Review: Modelling Optimal Location for Electric Vehicle Charging Station based on Existing Power Grid Capacity

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Abstract

The adoption of electric vehicles by consumers is directly dependent on the accessibility to EV charging stations. The location of the EV charging station primarily depends on convenience and access to the customer and constraints on the existing power grid. While there are several studies that focus on optimizing the location of EV charging stations based on proximity to the customer thereby improving the convenience and access, the real-world scenario of optimizing the location of EV charging stations at the current state depends more on the constraints on the existing power grids capacity to supply power to these stations without overloading the grid infrastructure. This research focusses on using the location-allocation model or fixed-charge model to determine the number of charging stations that can be allocated based on the surplus capacity of the power grid and p-median model to optimize the location of the charging stations to improve convenience of access to the customers.

Introduction

The Australian government has been taking considerable actions to promote the use of electric vehicles. A primary issue hindering the adoption of electric vehicles is the ability to recharge them with the same convenience as combustion engine vehicles. This problem has attracted several research focussing on identifying optimal locations for placing electric vehicle charging stations considering many factors.

Majority of the studies attempt to determine suitable locations for the electric charging stations based on the travel and refuelling pattern of combustion engine vehicles. However, the usage pattern and behaviour of electric vehicle drivers and combustion engine drivers vary greatly. The charging process of electric vehicle also varies greatly from a combustion engine vehicle in terms of time required to achieve similar mileage (Bálint Csonka, 2018). Owners of hybrid vehicles combining both forms of fuel preferred to recharge at workspaces while battery electric vehicle owners preferred home charging (Scott Hardman, 2018) (Patrick Morrissey, Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour, 2016). This behavior was driven by the concern for unavailability of charging ports at workplace or public charging stations and the time constraint (Nicholas, 2015).It was determined by a study by (Patrick Morrissey, Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour, 2016) that at present, charging at home is the preferred charging habit of electric vehicle owners followed by public and workplace charging. There are several other driver behaviour that needs to be understood for optimally locating electric charging stations (Long Pan, 2019).

The cost of charging at the various locations play a crucial role in the choice of charging location such as workplace, home or public charging facilities (Debapriya Chakraborty, 2019).

Different charging locations have need for different research approaches as the charging location is mostly fixed with longer availability of charging time at home and workplace, while the same is not the case with public locations (Zhaomiao Guo, 2016). With increase in deployment of electric vehicles there could be potential problems expected in the existing power networks, which under certain conditions may lead to power quality problems and voltage imbalance (Putrus G. A.).

The problem we attempt to solve in this study is determine the optimal location of electric charging stations with respect to the capacity of the existing power grids, and to understand the number of electric vehicles that can use public charging stations without overloading the power grid at peak usage times. Fast charging is critical for customers who would opt to charge at a public charging station (Keisuke Nansai, 2001). Wide-spread adoption of EVs depends on the location and sizing of fast charging stations. Construction of fast charging stations in turn depend on capacity available and estimated return on investment (Payam Sadeghi-Barzani, 2014). Fast charging requires dedicated hardware to meet the demand, which in turn would increase the load on the power grid. To solve this, first approach would be using fixed charge model or location-allocation mode (Lin, 2014) that imposes a constraint on the maximum capacity available from the grid, expected demand based on output of a queueing model, while treating the demand from each EV to be a constant.

The adoption of electric vehicles by consumers is directly dependent on the accessibility to EV charging stations. The approach followed is to determine the locations in North Sydney and then plan the layout. This requires understanding the constraints to be considered during this research phase. As the research progresses, further constraints for consideration can be added and the models can be tweaked accordingly.

1. Location models

In this section we explore the relevant methodologies to locate a facility based on factors such demand, cost, wait time, charging time, traffic conditions, raw material availability, maximum capacity of the facility (extent of existing power grid capacity), etc.

1.1. p-median model

This method can be used to model the location of EV charging stations provided the operator is willing to invest based on the demand.

The p-median model can be considered as an optimization model to cluster points or entities. Knowing the demand areas and assuming either the demands are equal or ignoring the demands, this model can be used to determine points to locate a facility such that it meets the demand with minimum distance of transportation for the consumer. Based on the number of facilities (medians) the operator is willing to set up, the p-median model can be used to identify layouts within a chosen location.

Consider a distance matrix d_{ij} such that it defines the distance between all i and j, and p is the number of medians/facilities. This model can be used to optimize the selection of the facilities in the location such that it reduces the overall distance between any i and j.

$X_{jj} = 1$ if j is a median and attached to itself, 0 otherwise. $X_{ij} = 1$ if i is not a median and is attached to a median j.

Then the constraints are:

I. $\sum_{j=1}^{n} X_{jj} = p$, where n is the number of potential layouts within the location. This constraint limits the number of medians as declared.

II. $\sum_{j=1}^{n} X_{ij} = 1 \; \forall \; i$

III. $X_{ij} \leq X_{jj} \; \forall \; i, j$

The second and third constraints ensure that each point is attached to only one other point if a non-median or self if a median.

Thus, total number of constraints would be $1 + n + n^2$.

To identify the ideal layout points, the objective function has to reduce the distance between any two points i and j, i.e., minimize $\sum\sum d_{ij} X_{ij}$. There are several heuristic solutions available to solve the p-median problem, as enumerating over $\binom{n}{p}$ ways is a computationally expensive task.

1.2. Location-allocation model

This model can be used when there are potential location or layout points and there is a need to identify best suited layouts with any predefined restrictions on capacity, demands, cost, etc.

Consider locating a facility at i from m potential locations, then there is a fixed cost f_i for locating the facility and a maximum capacity constraint C_i. Suppose there is a demand point j from n demand points, then the demand that needs to be met is defined by D_j. The cost functions between i and j can be modelled as c_{ij}. Then, $Y_i = 1$ when i is chosen and X_{ij} is the quantity transferred between the two points.

Now, the objective function would have two costs namely, cost of location and cost of allocation of capacity for each of the demand points.

Minimize $\sum_{i=1}^{m} f_i Y_i + \sum_{I=1}^{m} \sum_{j=1}^{n} c_{ij} X_{ij}$

Constraints can be declared as,

I. $\sum_{i=1}^{m} Y_i = k$

This constraint can be used when the number of locations has to be limited to a certain value of k.

II. Since each facility has a capacity specified by C_i, $\sum_{j=1}^{n} X_{ij} \leq C_i Y_i$

This constraint can be used to determine whether a chosen facility ($Y_i = 1$) has the capacity required to meet the demand of the point (EV in our case).

III. $\sum_i X_{ij} \geq D_j$, since each demand point can only receive maximum or lesser than its maximum demand (charging requirement of an EV in our case).

By removing the first constraint, the model (with some changes) can automatically determine the optimum number of stations required.

2. Constraints

The constraints for our research are average queueing length, capacity of existing electrical network in the selected locations for setting up the facilities.

2.1. Average queueing length

The average queuing length for charging electric vehicles has been modelled recently in (Grigorev et. All, 2021), (Patel et all, 2021) in which the authors consider several methods for modelling queue qaiting times at charging facilities, including transport modelling outputs and energy substantion capacity datasets. The number of vehicles waiting to enter a charging facility can influence the waiting times and the charging inside the station given its restricted number of charging plots.

2.2. Capacity of existing electrical network

The below table categorizes the EV charging stations into 4 types based on their capacity and infrastructure requirement, according to definitions in Queensland, Australia (see Queensland Government, 2020).

Charging category	Type	Capacity & consumption per charge	Location	Infrastructure review requirement
Basic	AC	2.4 kW – 7 kW 10 – 35 kWh	Typical home parking	
Destination	AC	11 kW – 22 kW 8 – 32 kWh	Malls, charging facilities, etc.	Properties electrical infrastructure. Network impact unlikely.
Fast	DC	50 kW – 150 kW 15 – 90 kWh	Typical parking in major transport routes	Electrical network capacity study required. Location near high power transformer.
Ultrafast	DC	150 kW – 350 kW 20 – 100 kWh	National highways	Require significant investment in local electrical network.

Electricity networks must safely deliver the amount of electricity required by commercial and residential establishments. At certain occasions, the existing network may not be able to operate to meet the capacity requirement when the demand for power is high. At such instances, AEMO adopts **load shedding** (also known as rotating outages or power sharing) which is an interruption in the supply of power in a planned and co-ordinated way (see guidelines in (AEMO, 2020)).

Conclusion

The above investigations have been taken into consideration and the modelling outputs have been published in (Grigorev et. All, 2021). For reducing the description in this tehcnical report, we redirect the reader to the above manuscript. Also, an important future direction of this study is to include an optimal location of new EV charging stations inside the network, and simulate their impact via a combined simulation and queue modelling approach, with constraints on the energy substation capacity. Several hybrid approach of mixing traffic simulation with data driven algorithsm and even air quality monitoring can be found in several publsihed works from (Mihaita et. All, 2019), (Ou et all, 2020), (Shafiei et. All, 2020), etc.

Bibliography

Bálint Csonka, C. C. (2018). Determination of charging infrastructure location for electric vehicles.

Debapriya Chakraborty, D. S. (2019). Demand drivers for charging infrastructure-charging behavior of plug-in electric vehicle commuters, Transportation Research Part D: Transport and Environment, Volume 76.

Keisuke Nansai, S. T. (2001). Life-cycle analysis of charging infrastructure for electric vehicles.

Lin, C. K. (2014). Solving a Location, Allocation, and Capacity Planning Problem with Dynamic Demand and Response Time Service Level.

Long Pan, E. Y. (2019). A location model for electric vehicle (EV) public charging stations based on drivers' existing activities.

Nicholas, M. T. (2015). Charging for Charging at Work: Increasing the Availability of Charging Through Pricing.

Patrick Morrissey, P. W. (2016). Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour.

Patrick Morrissey, P. W. (2016). Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour.

Payam Sadeghi-Barzani, A. R.-G.-K. (2014). Optimal fast charging station placing and sizing.

Putrus G. A., S. P. (n.d.). Impact of Electric Vehicles on Power Distribution Networks.

Scott Hardman, A. J. (2018). A review of consumer preferences of and interactions with electric vehicle charging infrastructure, Transportation Research Part D: Transport and Environment.

Zhaomiao Guo, J. D. (2016). Infrastructure planning for fast charging stations in a competitive market.

Yuming Ou, Adriana-Simona Mihăiţă, Fang Chen,14 - Big data processing and analysis on the impact of COVID-19 on public transport delay, Editor(s): Utku Kose, Deepak Gupta, Victor Hugo C. de Albuquerque, Ashish Khanna, Data Science for COVID-19, Academic Press, 2021, Pages 257-278, ISBN 9780323907699, https://doi.org/10.1016/B978-0-323-90769-9.00010-4.

Shafiei, S.; Mihaita, A.S.; Nguyen, H.; Cai, C.; Integrating data-driven and simulation models to predict traffic state affected by road incidents, Transportation Letters: the International Journal of Transportation Research (IF=1.84), DOI: 10.1080/19427867.2021.1916284, ISSN: 1942-7867, 14th of April 2021.

Tuo Mao, Adriana-Simona Mihăită, Fang Chen, and Hai L. Vu. 2022. Boosted Genetic Algorithm Using Machine Learning for Traffic Control Optimization. Trans. Intell. Transport. Sys. 23, 7 (July 2022), 7112–7141. https://doi.org/10.1109/TITS.2021.3066958, (IF = 6.49, H5 = 92, number one top publication ranking from Google Scholar in transportation domain), Mihaita A. S., Dupont L., Cherry O., Camargo M., Cai C., Evaluating air quality inside an eco-neighbourhood by combining stationary and smart mobile pollution, Journal of Cleaner Production (JCLP), Vol. 221, pp 398-418, ISSN = 0959-6526, https://doi.org/10.1016/j.jclepro.2019.02.179, (IF = 7.24, H5 = 154, place 42/100 top rated venues in Google scholar).

Mihaita A. S., Benavides, M., Camargo, C. Cai, Predicting air quality by integrating a mesoscopic traffic simulation model and air pollutant estimation models, International Journal of Intelligent Transportation System Research (IJITSR), DOI: 10.1007/s13177-018-0160-z, Online ISSN1868-8659, 15 May 2019, Volume 17, Issue 2, pp 125–141.

Mihaita A. S., Dupont L., Camargo M., Multi-objective traffic signal optimization using 3D mesoscopic simulation and evolutionary algorithms, Simulation Modelling Practice and Theory (SIMPAT), https://doi.org/10.1016/j.simpat.2018.05.005, Volume 86, August 2018, Pages 120-138.

Wen T, Mihăiţă A-S, Nguyen H, Cai C, Chen F. Integrated Incident Decision-Support using Traffic Simulation and Data-Driven Models. Transportation Research Record. 2018;2672(42):247-256. doi:10.1177/0361198118782270.

Mihaita A.S., Mocanu S., Lhoste, P., "Probabilistic analysis of a class of continuous-time stochastic switching systems with event-driven control", European Journal of Automation (JESA), July 2016.

Monticolo, D., Mihaita, A.S., Darwich, H., Hilaire, V., "An Agent Based System to build project memories during engineering projects", Knowledge Based Systems Journal (KBS), January 2014.

Monticolo, D. Mihaita A.S. "A multi Agent System to Manage Ideas during Collaborative Creativity Workshops", International Journal of Future Computer and Communication (IJFCC), vol 3., nr 1, February 2014, P66-71, (extended version of the paper presented in ICFCC 2013).

Mihaita A.S., Mocanu S., "Simulation en temps continu pour la commande orientée événements des systèmes stochastiques à commutation", European Journal of Automation (JESA), 45 1-3 (157-172), Oct 2011. (selected for publication after the MSR Conference Lille 2011).

R. Patel, G. Trivedi, D. R. Vyas, A. -S. Mihaita and S. Padmanaban, "Framework for User-Centered Access to Electric Charging Facilities via Energy-Trading Blockchain," 2021 24th International Symposium on Wireless Personal Multimedia Communications (WPMC), 2021, pp. 1-6, doi: 10.1109/WPMC52694.2021.9700475.

Artur Grigorev, Tuo Mao, Adam Berry, Joachim Tan, Loki Purushothaman, and Adriana-Simona Mihaita. 2021. How will electric vehicles affect traffic congestion and energy consumption: an integrated modelling approach. In 2021 IEEE International

Intelligent Transportation Systems Conference (ITSC). IEEE Press, 1635–1642. https://dl.acm.org/doi/abs/10.1109/ITSC48978.2021.9564561

Grigorev, Ar., Lee, S., Ch, F., Mihaita, A.S., Modelling impact of traffic disruptions by using machine learning methods, Transport Research Association for NSW Symposium, 18th of November 2020.

Adriana-Simona Mihaita, Zac Papachatgis, and Marian-Andrei Rizoiu. 2020. Graph modelling approaches for motorway traffic flow prediction. In 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC). IEEE Press, 1–8. https://dl.acm.org/doi/abs/10.1109/ITSC45102.2020.9294744.

Y. Ou, A. -S. Mihaita and F. Chen, "Dynamic Train Demand Estimation and Passenger Assignment," 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), 2020, pp. 1-6, doi: 10.1109/ITSC45102.2020.9294606.20

Shafiei, Sajjad, Mihaita, A.S., Nguyen, Hoang, Bentley, Christopher D B, Cai, Chen, Short-Term Traffic Prediction under Non-Recurrent Incident Conditions Integrating Data-Driven Models and Traffic Simulation, Transportation Research Board (TRB) 99th Annual Meeting, Washington D.C., Jan 2020, http://hdl.handle.net/10453/138721.

A-S. Mihaita, H. Li, Z. He and M. -A. Rizoiu, "Motorway Traffic Flow Prediction using Advanced Deep Learning," 2019 IEEE Intelligent Transportation Systems Conference (ITSC), 2019, pp. 1683-1690, doi: 10.1109/ITSC.2019.8916852.

Mihaita, A.S., Liu, Z., Cai, C., Rizoiu, M.A "Arterial incident duration prediction using a bi-level framework of extreme gradient-tree boosting", ITS World Congress 2019, Singapore, 21-25 Oct 2019.

Mao, T., Mihaita, A.S., Cai, C., Traffic Signal Control Optimisation under Severe Incident Conditions using Genetic Algorithm, ITS World Congress 2019, Singapore, 21-25 Oct 2019.

Shaffiei, S. Mihaita, A.S., Cai, C., Demand Estimation and Prediction for Short-term Traffic Forecasting in Existence of Non-recurrent Incidents, ITS World Congress 2019, Singapore, 21-25 Oct 2019.

Mihaita A. S., Dupont L., Cherry O., Camargo M., Cai C., Air quality monitoring using stationary versus mobile sensing units: a case study from Lorraine, France, 25th ITS World Congress (ITSWC 2018), Copenhagen, Denmark, 17-21st of September 2018.

Wen Tao, Mihaita A.S., Nguyen Hoang, Cai Chen, Integrated Incident decision support using traffic simulation and data-driven models. Transportation Research Board 97th Annual Meeting (TRB 2018), Washington D.C., January 7-11, 2018, H5=48.

Mihaita A. S., Tyler Paul, Wall John, Vecovsky Vanessa, Cai Chen, Positioning and collision alert investigation for DSRC-equipped light vehicles through a case study in CITI, 24th

World Congress on Intelligent Transportation Systems (ITSWC 2017), Montreal, Canada, 29 October - 2 November 2017.

Mihaita A. S, Cai Chen, Chen Fang, Event-triggered control for improving the positioning accuracy of connected vehicles equipped with DSRC, International Federation of Automatic Control World Congress (IFAC WC 2017), 9-14 July 2017, Toulouse, France.

Mihaita A. S, Tyler Paul, Menon Aditya, Wen Tao, Ou Yuming, Cai Chen, Chen Fang, "An investigation of positioning accuracy transmitted by connected heavy vehicles using DSRC", Transportation Research Board 96th Annual Meeting (TRB 2017), Washington D.C., January 8-12, Paper number 17-03863, 2017, https://pubsindex.trb.org/view/2017/C/1438533.

Mihaita A. S., Benavides, M., Camargo, M., "Integrating a mesoscopic traffic simulation model and a simplified NO2 estimation model", 23rd World Congress on Intelligent Transportation Systems (ITSWC 2016), Melbourne, Australia, 10-14 October 2016.

Mihaita A.S., Camargo, M., Lhoste, P. , " Evaluating the impact of the traffic reconfiguration of a complex urban intersection ", 10th International Conference on Modelling, Optimization and Simulation (MOSIM 2014), Nancy, France, 5-7 November 2014 (accepted on 18th of July 2014).

Mihaita A.S., Camargo, M., Lhoste, P. "Optimization of a complex urban intersection using discrete-event simulation and evolutionary algorithms", International Federation of Automatic Control World Congress (IFAC WC 2014), Cape Town, Africa, 24-29 August 2014.

Issa, F., Monticolo, D., Gabriel, A. , Mihaita, A.S., "An Intelligent System based on Natural Language Processing to support the brain purge in the creativity process", IAENG International Conference on Artificial Intelligence and Applications (ICAIA 2014), Hong Kong, 12-14 March, 2014.

Monticolo, D., Mihaita A.S., "A Multi Agent System to manage ideas during Collaborative Creativity Workshops", 5th International Conference on Future Computer and Communication (ICFCC 2013), Phuket, Thailand, 26 May 2013.

Mihaita A. S., Mocanu S., "Un nouveau modéle de l'énergie de commande des systèmes stochastiques à commutation", Septième Conférence Internationale Francophone d'Automatique (CIFA 2012) Grenoble, France, 4-7th of July.

Mihaita A. S., Mocanu S., "An Energy Model for the Event-Based Control of a Switched Integrator", International Federation of Automatic Control World Congress (IFAC WC 2011), Milano, September 2011.

Queensland Government, Practice Note on Electric Vehicle charging, 2020. Online, https://www.dsdmip.qld.gov.au/resources/guideline/pda/practice-note-electric-vehicle-charging.pdf.

AEMO, Lead shedding fact sheet, 2020, online https://aemo.com.au/-/media/media-hub/infographics/load-shedding-fact-sheet.pdf?la=en.