Energy Consumption Model and Charging Station Placement for Electric Vehicles

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Abstract: A detailed energy consumption model is introduced for electric vehicles (EVs), that takes into account all tractive effort components, regenerative braking, and parasitic power users. Based on this model a software tool for EV reachable range estimation (EVRE) is developed and implemented. This software tool uses real driving distances and elevation data from Google Maps and can therefore much more accurate predict the reachable range of a given EV than the typical Euclidean distance models. Furthermore, an optimization model for the placement of charging stations to maximize the number of reachable households under energy constraints is established using EVRE. These results are illustrated by a number of examples involving the cities of New York City, Boulder Colorado, and South Bend, Indiana. The developed methodology can easily incorporate additional constraints such as popular destinations, preferred parking, driver habits, available power infrastructure, etc. to initially reduce the search space for optimal charging station placement.

1 INTRODUCTION

Advances in battery technology have already put a significant number of electric vehicles on the road (Dickerman and Harrison, 2010). Innovative technologies to reduce manufacturing costs and increase battery capacity are needed to make such vehicles more appealing to the public. Allowing EV users to reach charging stations conveniently is crucial for the popularization of electric vehicles.

For accurately predicting and simulating vehicle range, an accurate energy consumption model based on the tractive effort is needed. Simplified EV power train models were developed for new and existing production vehicles(Hayes et al., 2011). An energy usage model based on tractive effort has been constructed for electrically powered utility vehicles traveling a route with significant elevation variations(Prins et al., 2012). In our energy consumption model, a more detailed tractive effort model is provided. The driving distances and elevation data for routes on Google Maps are used in an infrastructure model for increased accuracy.

The problem of charging station placement has been investigated by many researchers. A maximal coverage model to optimize the demand covered within an acceptable level of service has been investigated in (Frade et al., 2011). An optimization model was developed to maximize total fleet-wide charging levels for the location of a public EV charging infrastructure (Xi et al., 2013). In (Ge et al., 2011), a grid partition method has been investigated for locating, sizing and service area division of the charging stations. A two-step clustering process was proposed in (Ip et al., 2010) for optimizing the allocation of fast charging stations. A coordinated clustering algorithms was programmed for mapping the charging infrastructures in (Momtazpour et al., 2012). (Andrews et al., 2013) studied how EV would perform in meeting the driving needs of vehicle owners and then proposed an optimization model based on a user charging model to find locations for charging stations. In (Lam et al., 2013), the electric vehicle charging station placement problem was formulated to minimize the total construction cost subject to the constraints for the charging station coverage and the convenience of the drivers for EV charging. The NP-hardness property of the problem was studied and an efficient greedy algorithm to tackle this problem was proposed. In (Wang et al., 2013) a location model of charging stations is established based on electricity consumption along the roads among cities. Furthermore a quantitative model of charging stations was presented based on the conversion of oil sales

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in a certain area. Driving patterns have been widely used to optimize the charging station placement. An agent-based decision support system was presented for identifying patterns in residential EV ownership and driving activities to enable strategic deployment of new charging infrastructure(Sweda and Klabjan, 2011). An improved charging station location solution was developed by providing behavioral models to predict when and where vehicles are likely to be parked (Chen et al., 2013). An optimization model based on driving patterns was proposed to find locations for charging stations needed to support EV usage (John et al.,). Another important method is based on the Voronoi diagram. In(Koyanagi and Yokoyama, 2010) and (Koyanagi et al., 2001), the candidates of charging facilities for EVs were analyzed by using Voronoi diagrams for the equilibrium arrangement in Musashino city. In (Feng et al., 2012), a weighted Voronoi diagram was used for the research of locating, sizing and service area division of the charging stations. The problem with Voronoi diagrams is that Euclidean distance is used instead of the real driving distance.

The placement of charging stations can be approached from a number of different angles, that may for example include the energy deficit of EVs, the available power infrastructure, popular parking locations and stay times, minimizing overall energy, minimizing congestion, etc. We address the problem of optimal charging station placement from the viewpoint of reaching the most customers or households, i.e. something a private charging station owner would typically consider. On the other hand, this problem is also of interest for municipalities, power companies, and federal agencies such as the environmental protection agency and the department of transportation. The developed concept can easily be used in conjunction with the other above mentioned criteria, if the placement methods based on these criteria can narrow down the number of possible locations for charging station placement a priori. Therefore, these criteria would be used in form of location constraints. In this paper, the optimization problem for charging station placement is investigated based on an EV energy consumption model including driving distance and elevation. Given an energy bound, the corresponding reachable contures in Google Maps for different possible charging station centers are determined. Maximizing the number of households in this range is discussed subsequently.

This paper is organized as follows. In Section 2, the energy model for EVs is presented. In Section 3, an optimization model for charging station placement is provided. The simulation results are discussed in Section 4. Conclusions are provided in Section 5.

2 ENERGY MODELS FOR ELECTRIC VEHICLES

In this section we will introduce a detailed energy consumption model that has two main components: a tractive effort model with air drag, rolling resistance, acceleration, and hill climbing components, and a lumped loss model for the mechanical and electric powertrain, that is described by individual efficiencies of powertrain components. Together, both components provide a fairly accurate description of the energy usage of an EV in almost any driving situation.

The air drag power component is modeled by:

$$P_{air}(t) = \frac{1}{2}\rho C_d A\left(\frac{ds(t)}{dt}\right)^3 \tag{1}$$

where A is frontal cross sectional area, ρ the density of air, C_d is the drag coefficient, $s(t)$ is the driving distance, $\frac{ds(t)}{dt}$ is the corresponding velocity at time t.

The rolling resistance power component is modeled by:

$$P_{roll}(t) = f_r M g \frac{ds(t)}{dt} \tag{2}$$

where f_r is the coefficient of rolling resistance, M is the mass of the EV, g is the gravitational acceleration, which is 9.81 m/s^2.

The hill climbing power component is given by:

$$P_{hill}(t) = Mg\frac{dh(t)}{dt} \tag{3}$$

where $h(t)$ is the elevation at t, $\frac{dh(t)}{dt}$ is the vertical velocity component.

The acceleration power component is given by:

$$P_{ac}(t) = M\frac{d^2s(t)}{dt^2}\frac{ds(t)}{dt} \tag{4}$$

where $\frac{d^2s(t)}{dt^2}$ is the acceleration at time t.

The efficiencies of battery, power converter, e-motor controller, e-motor and mechanical powertrain are denoted by η_{bat}, η_{conv}, η_{contr}, η_m, η_{mp} respectively.

Therefore, the overall propulsion power balance equation can be written as:

$$\begin{aligned} &P_{bat}(t)\eta_{bat}\eta_{conv}\eta_{contr}\eta_m\eta_{mp} \\ &= P_{air}(t) + P_{roll}(t) + P_{hill}(t) + P_{ac}(t) \end{aligned} \tag{5}$$

Now denoting parasitic power losses at the battery (lights, heater, stereo, etc.) as P_{para}, we obtain:

$$\begin{aligned}&(P_{bat}(t) - P_{para}(t))\eta_{bat}\eta_{conv}\eta_{contr}\eta_m\eta_{mp} \\ &= P_{air}(t) + P_{roll}(t) + P_{hill}(t) + P_{ac}(t)\end{aligned} \tag{6}$$

In the case of regenerative braking we need to reverse the powerflow and hence use the following modification of the above equation:

$$\begin{aligned}&P_{bat}(t) - P_{para}(t) \\ &= (P_{air}(t) + P_{roll}(t) + P_{hill}(t) + P_{ac}(t))\eta_{bat}\eta_{conv}\eta_{contr}\eta_m\eta_{mp}\end{aligned} \tag{7}$$

with η_{bat}, η_{conv}, η_{contr}, η_m, η_{mp} being the efficiencies of the respective components for reversed powerflow.

3 OPTIMIZATION FOR CHARGING STATION PLACEMENT

The optimal placement of charging stations has been intensely researched and many methods have been developed((Xi et al., 2013),(Chen et al., 2013),(Feng et al., 2012),(Frade et al., 2011),(Sweda and Klabjan, 2011),(Koyanagi and Yokoyama, 2010)). This method is based on the energy consumption model of electric vehicles. We focus on maximizing the reachable households with a given battery energy bound. Given this constraint, the reachable range can be derived on Google Maps. To get the amount of covered population in the reachable range, the population distribution for the considered area must be known. A reasonable way is to divide the city by ZIP code zones and then use the population in each ZIP code area.

Suppose there are N possible positions $X = \{x_1, \ldots, x_N\}$ for charging station placement. There are M ZIP code zones $Y = \{y_1, \ldots, y_M\}$. The model for a ZIP code zone is $y_j = (ycp_j, ypop_j)$, where ycp_j is the center position of y_j and $ypop_j$ is the population number of y_j. For each possible position x_i, function $Range(x_i, E_{bound})$ is used to get its reachable range R_i, where E_{bound} is the energy bound constraint. This range can be obtained by the software tool EVRE, which is implemented based on Google Maps Javascript API. Define $Z_{ik} = (Zpos_{ik}, Zpop_{ik})$ as the kth ZIP code zone covered by range R_i, where $Zpos_{ik}$ is the center position and $Zpop_{ik}$ is the population number. Then we can get the following optimization model for maximizing reachable households.

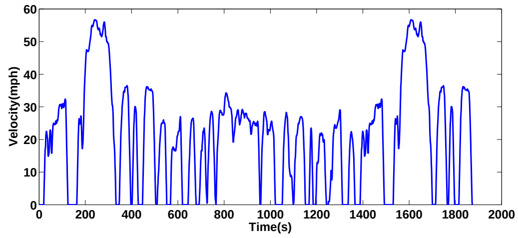

Figure 1: FTP-75 Driving Cycle.

$$\begin{aligned}\underset{Z_i}{\text{Maximize}} \quad & \sum_k Zpop_{ik} \\ \text{subject to} \quad & x_i \in X = \{x_1, \ldots, x_N\} \\ & y_j \in Y = \{y_1, \ldots, y_M\} \\ & R_i = Range(x_i,\ E_{bound}) \\ & Z_i = \{Z_{ik} | Z_{ik} \in Y \text{ and } Zpos_{ik} \in R_i\} \\ & i = 1, \ldots, N;\ j = 1, \ldots, M;\ 1 \leq k \leq M\end{aligned} \tag{8}$$

Model (8) is easy to implement, but only the center position is used to represent the whole ZIP code zone, which may cause errors when the center lies near the boundary of the range. To obtain a more accurate, implementable and computable optimization model, each ZIP code zone can be further divided into subareas.

4 SIMULATION RESULTS

4.1 Reachable Range Estimation

The electric vehicle reachable range estimation(EVRE) software tool is implemented based on the Google Maps API (Google,) by applying the energy model we constructed.

To estimate the reachable range, the driving distance, elevation data and velocity information are needed. The driving distance and elevation data along the route between two positions on Google Maps can be obtained directly using the corresponding APIs. FTP-75 driving cycle in Figure 1 is used to mimic the driving velocity for EVs in the urban area, which are a series of tests defined by the US Environmental Protection Agency (EPA). It consists of starting with a cold engine and making 23 stops over a period of 31 minutes for an average speed of 20 mph and with a top speed of 56 mph. The average velocity derived from the driving distance and duration information is used for the suburban area. With this data, the energy consumption can be calculated by applying the energy model.

Given the energy constraint, the reachable range is represented by a polygon and a breadth-first search method is used to estimate it by determining its vertices. In each search step, a set of positions on one circle serves as the possible origins and the charging station position is the destination. Each pair (origin and destination) has its corresponding energy consumption value. Comparing them with the energy constraint is done to judge whether these positions can be the vertices of the reachable range polygon. Different radii of the circles for these possible positions are used in different steps. Once all the vertices are found, the searching process is complete and the reachable range is determined.

Tesla Model S is selected as the electric vehicle prototype. Its mass is 2108 kg, frontal area is 2 m^2, drag coefficient is 0.24, rolling resistance coefficient is 0.01, battery capacity is 85 kWh and nominal range is 265 mile.

Boulder, Co and New York City are selected as the example areas. These two cities have different terrains. Boulder is a small city with many mountains on the westside with drastic elevation changes. New York City is a metropolis with a complicated street system and less elevation changes. Since our model considers the real driving distance and elevation, the reachable range is expected to be totally different.

Given the battery energy bound 2 kWh, the reachable range (charging station is marked as the center and serves as destination) in Figure 2 is derived using EVRE. Both of the ranges are unsymmetric, because different driving directions have different routes and elevation in both cities. Figure 2 shows that the reachable range in Boulder is much larger than in New York City. There are at least two reasons for it. First, the driving direction is from positions outside of the city center. In Boulder, there are many downhill routes, which casuses the EVs to have a larger driving range, because the EV's regenerative braking plays a dominant roll. While in New York City, there is less potential energy reused with little elevation change. Second, New York City's complicated street system makes the EV's velocity more like the FTP-75 cycle. There are many accelerations and decelerations, which will be a large energy cost. Hence, under the same energy bound constraint, the reachable range in New York is much smaller than in Boulder.

Figure 2 also shows the comparison results with the Euclidean model. The Euclidean model is typically calculated using the following method.

$$\frac{Range}{Capacity} = \frac{265mile}{85kWh} = 3.12mile/kWh$$

Two concentric circles are set in Fig. 2, one with radius 3.12 miles, the other with radius 6.24 miles for a energy bound of 2 kWh. The reachable range

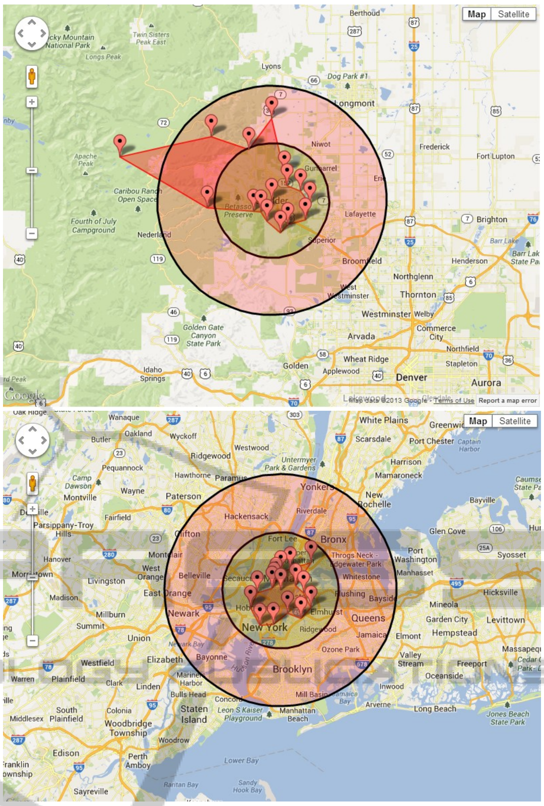

Figure 2: Top:Reachable range estimation(2kWh)in Boulder Bottom:Reachable range estimation(2kWh)in New York.

derived from EVRE is significantly different from the range created by the Euclidean model. Because driving distance and elevation data are considered, our model and software can provide a more accurate range for EVs than the Euclidean model.

The intersection area is shown in Figure 3, the red coverage is obtained by traveling from the suburban area to the charging station center in the city; the blue coverage is obtained by traveling in the opposite direction. The elevation is changed when the route direction is reversed, which makes the energy consumption unsymmetric with regard to direction, especially in Boulder. There are many other factors that change, for example, the route choice(there are many one-ways in New York.) Hence we can get two different coverage areas. From Figure 3, we can see that the difference in Boulder is much larger than that in New York. This shows the elevation change is responsible for the energy consumption difference when reversing the driving direction. The intersection for these two coverage areas is where EVs can commute between its position and the charging station by using up to 2 kWh energy. The intersection area should be the real coverage range for the corresponding charging station

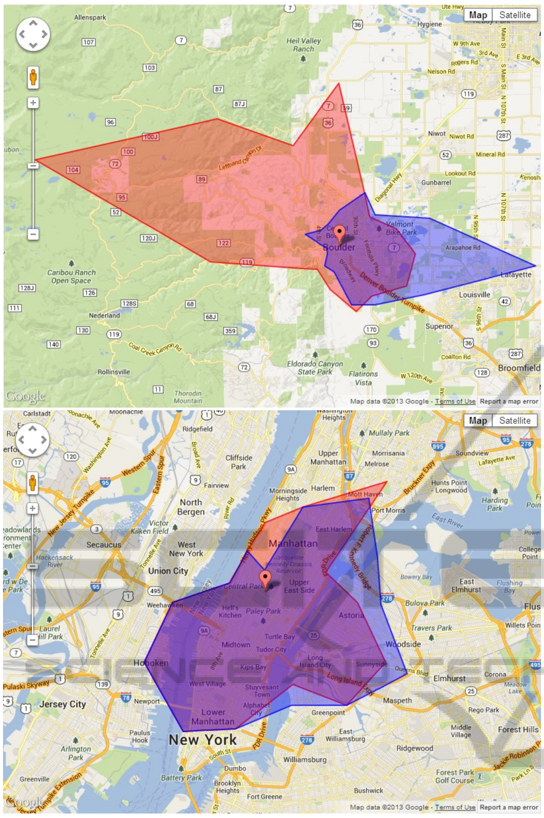

Figure 3: Top:Intersection Area in Boulder(2kWh) Bottom: Intersection Area in New York(2kWh).

considered by the EV owner.

Figure 4 shows the results with different energy radii for these two cities. Each coverage area represents a reachable range with the given amount of energy. Three kinds of energy radii are considered: 2 kWh, 3 kWh and 4 kWh. Figure 4 shows that these coverage areas are no longer concentric circles, they become irregular and the resulting polygons are not similar for the different energy levels.

4.2 Charging Station Placement for South Bend

South Bend, IN, a midsize city in the US, is selected as a showcase area. As stated in the optimization model (8) , to model the population distribution, the area can be divided according to ZIP codes. There are 13 ZIP codes in South Bend area, which means $M = 13$. Table 1 includes the ZIP codes and their corresponding population information. For possible charging station positions, five possible places are selected as examples, which means $N = 5$. They are listed in Table 2. We need to choose one for these five possible positions to maximize the reachable population.

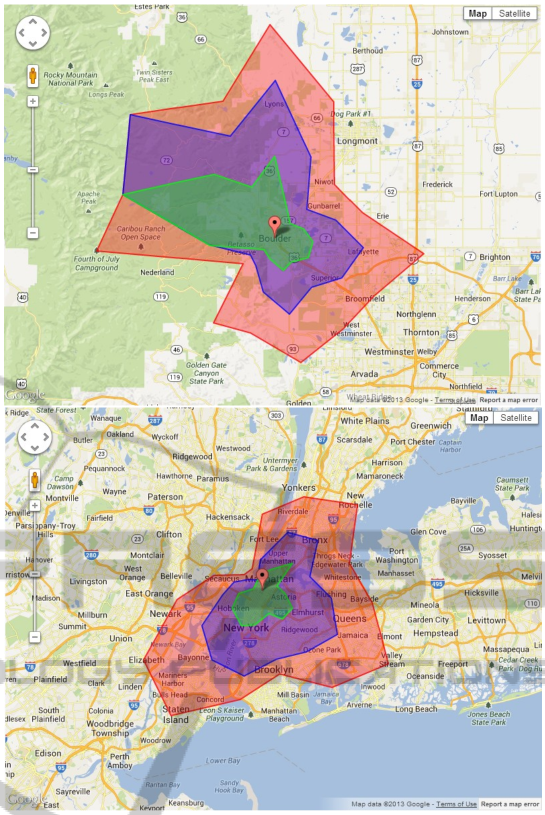

Figure 4: Top: Energy radius in Boulder, Bottom: Energy radius in New York (Green: 2kWh, Blue: 3kWh, Red: 4kWh).

Table 1: Population Distribution in South Bend.

Y	ZIP Code	Population
y_1	46544	30695
y_2	46545	28445
y_3	46556	7424
y_4	46601	8460
y_5	46613	11526
y_6	46614	27041
y_7	46615	16905
y_8	46616	6431
y_9	46617	11644
y_{10}	46619	22489
y_{11}	46628	25319
y_{12}	46635	4172
y_{13}	46637	13829

With these ZIP codes and their population information, EVRE is used to calculate the covered population for each possible position. The energy bound E_{bound} for the reachable range is 2 kWh. Figure 5 shows the coverage of two possible charging station positions, one is the Century Center and the other is

Table 2: Charging Station Placement in South Bend.

X	Possible Position	Covered Population
x_1	Century Center	187719
x_2	University of Notre Dame	97310
x_3	McKinley Town Center	125702
x_4	University Park Mall	62434
x_5	South Bend Airport	74225

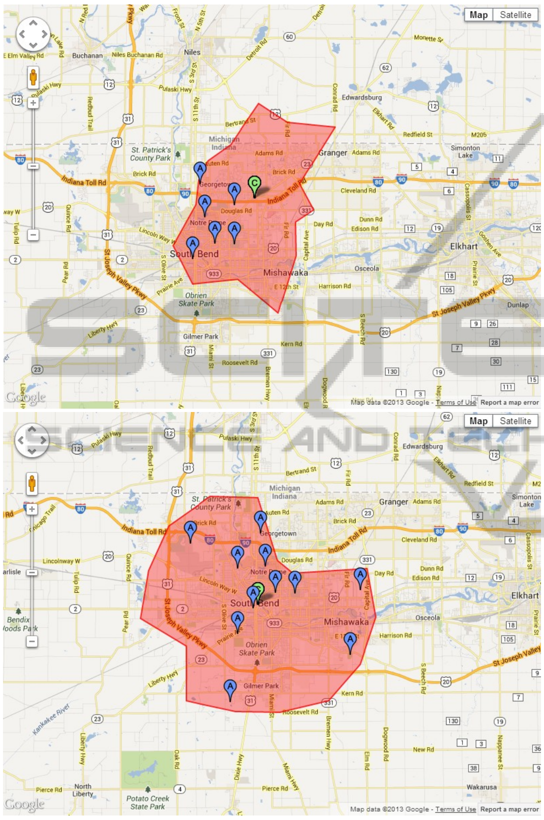

Figure 5: Coverage Range in South Bend, IN. Top: University Park Mall, Bottom: Century Center

the University Park Mall. The Blue markers are the centers of the covered ZIP code zones, and the green markers are the charging station positions. From Figure 5, we can see that they have different reachable ranges and will cover different ZIP code zones. After we know the covered ZIP code zones, we can calculate the corresponding covered population. The covered population is listed in Table 2.

From the results in Table 2, we can see that Century Center has the largest covered population, which means that under this gain function and the 2 kWh battery energy bound constraint, it is the best position to place the charging station among these five possible positions.

5 CONCLUSION

In this paper, a detailed energy consumption model for EVs has been introduced. It includes a vehicle as well as an infrastructure model aided by Google Maps. The combination of these two models allows to predict vehicle driving range in any geographic location supported by google maps. A software tool (EVRE) was developed that accurately predicts this driving range from a specified starting point or to a specified destination. In a second step, this software tool was used to solve the problem of optimally placing charging stations, with the goal to reach the maximum number of households. EVRE allows to solve this problem efficiently. In addition, the developed concept allows to perform other types of charging station optimizations and can take a number of practical constraints into account. In fact constraints such as power infrastucture, popular parking destinations, energy constraints, etc. can easily be incorporated to narrow down the initial search space for candidate locations of charging stations.

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REFERENCES

Andrews, M., Dogru, M. K., Hobby, J. D., Jin, Y., and Tucci, G. H. (2013). Modeling and optimization for electric vehicle charging infrastructure.

Chen, T. D., Kockelman, K. M., Khan, M., and Modeler, T. (2013). The electric vehicle charging station location problem: A parking-based assignment method for seattle. In *Transportation Research Board 92nd Annual Meeting*, number 13-1254.

Dickerman, L. and Harrison, J. (2010). A new car, a new grid. *Power and Energy Magazine, IEEE*, 8(2):55–61.

Feng, L., Ge, S., and Liu, H. (2012). Electric vehicle charging station planning based on weighted voronoi diagram. In *Power and Energy Engineering Conference (APPEEC), 2012 Asia-Pacific*, pages 1–5. IEEE.

Frade, I., Ribeiro, A., Gonçalves, G., and Antunes, A. P. (2011). Optimal location of charging stations for electric vehicles in a neighborhood in lisbon, portugal. *Transportation Research Record: Journal of the Transportation Research Board*, 2252(1):91–98.

Ge, S., Feng, L., and Liu, H. (2011). The planning of electric vehicle charging station based on grid partition method. In *Electrical and Control Engineering (ICECE), 2011 International Conference on*, pages 2726–2730. IEEE.

Google. Google maps javascript api v3. *https://developers.google.com/maps/documentation /javascript/tutorial*.

Hayes, J. G., de Oliveira, R. P. R., Vaughan, S., and Egan, M. G. (2011). Simplified electric vehicle power train models and range estimation. In *Vehicle Power and Propulsion Conference (VPPC), 2011 IEEE*, pages 1–5. IEEE.

Ip, A., Fong, S., and Liu, E. (2010). Optimization for allocating bev recharging stations in urban areas by using hierarchical clustering. In *Advanced Information Management and Service (IMS), 2010 6th International Conference on*, pages 460–465. IEEE.

John, M. A. M. K. D., Tucci, D. H. G. H., and Jin, Y. Modeling and optimization for electric vehicle charging infrastructure.

Koyanagi, F., Uriu, Y., and Yokoyama, R. (2001). Possibility of fuel cell fast charger and its arrangement problem for the infrastructure of electric vehicles. In *Power Tech Proceedings, 2001 IEEE Porto*, volume 4, pages 6–pp. IEEE.

Koyanagi, F. and Yokoyama, R. (2010). A priority order solution of ev recharger installation by domain division approach. In *Universities Power Engineering Conference (UPEC), 2010 45th International*, pages 1–8. IEEE.

Lam, A., Leung, Y.-W., and Chu, X. (2013). Electric vehicle charging station placement. In *Smart Grid Communications (SmartGridComm), 2013 IEEE International Conference on*, pages 510–515. IEEE.

Momtazpour, M., Butler, P., Hossain, M. S., Bozchalui, M. C., Ramakrishnan, N., and Sharma, R. (2012). Coordinated clustering algorithms to support charging infrastructure design for electric vehicles. In *Proceedings of the ACM SIGKDD International Workshop on Urban Computing*, pages 126–133. ACM.

Prins, R., Hurlbrink, R., and Winslow, L. (2012). Electric vehicle energy usage modeling and measurement. *International Journal of Modern Engineering*, 13(1):5–12.

Sweda, T. and Klabjan, D. (2011). An agent-based decision support system for electric vehicle charging infrastructure deployment. In *Vehicle Power and Propulsion Conference (VPPC), 2011 IEEE*, pages 1–5. IEEE.

Wang, Z., Liu, P., Cui, J., Xi, Y., and Zhang, L. (2013). Research on quantitative models of electric vehicle charging stations based on principle of energy equivalence. *Mathematical Problems in Engineering*, 2013.

Xi, X., Sioshansi, R., and Marano, V. (2013). Simulation–optimization model for location of a public electric vehicle charging infrastructure. *Transportation Research Part D: Transport and Environment*, 22:60–69.