

Charging Decision Making for Automated Electric Vehicles

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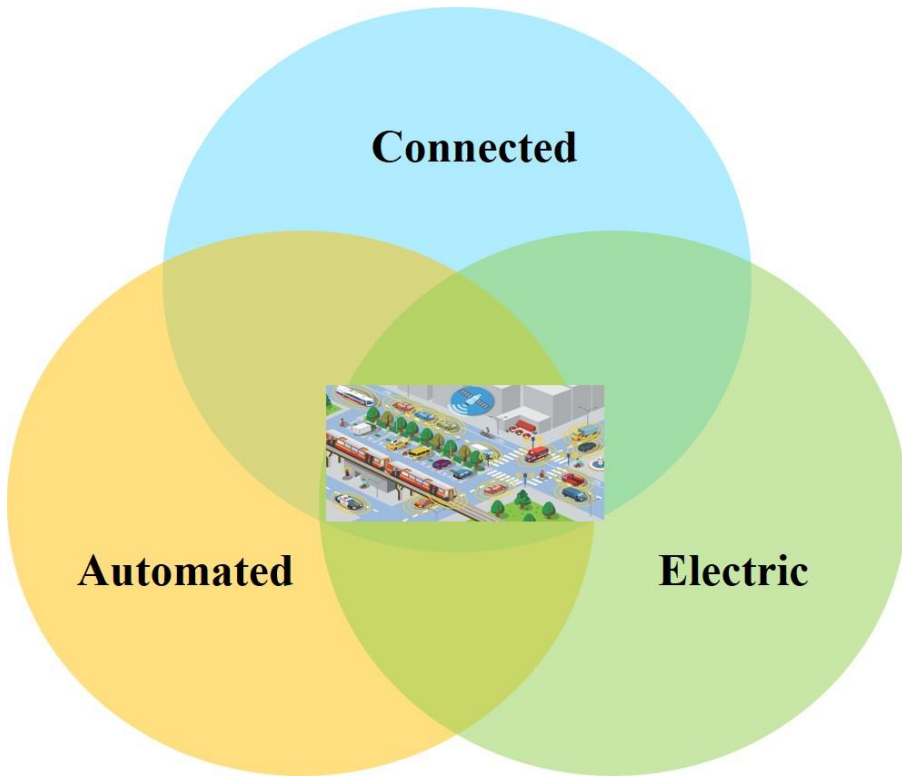
www.inl.gov



Automated Electric Vehicles

Convergence of the *Electric Propulsion Systems* and *Automated Vehicles*:

- Electric vehicles have inherent advantages when it comes to fuel savings and reducing the impact on the environment.
- It is easier for computers to drive electric vehicles.
- The lower operating cost of a battery-electric vehicle is a much bigger factor.

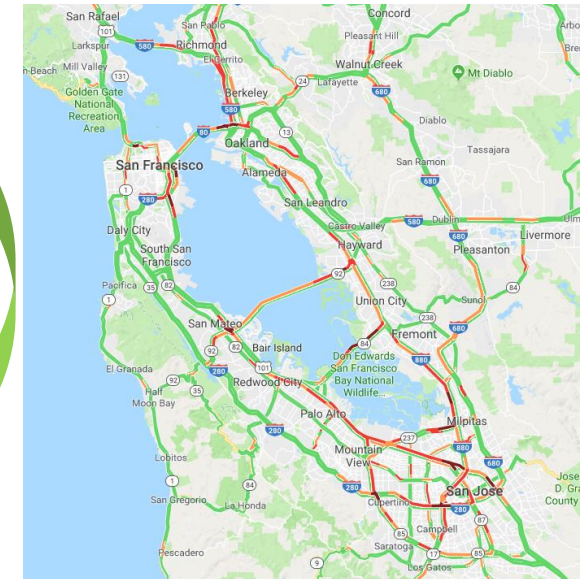
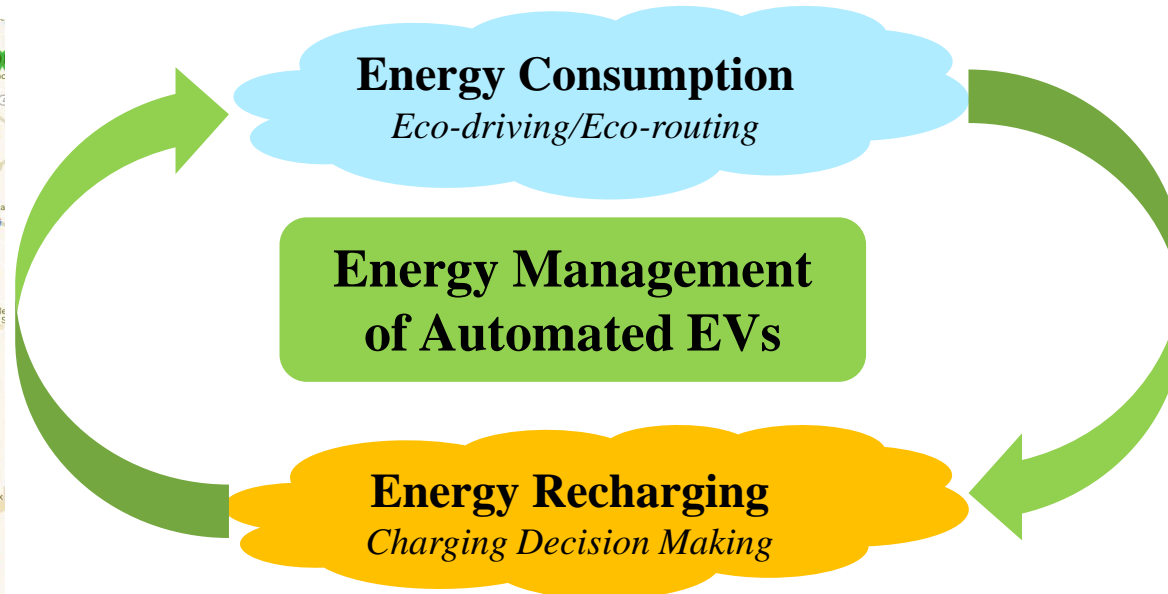
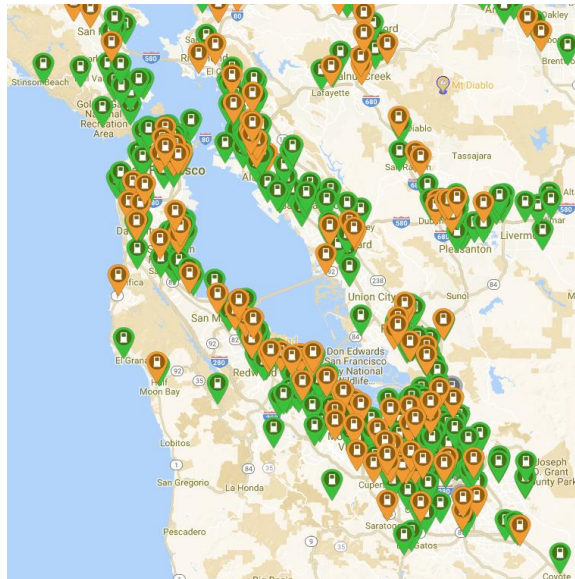


Hybrid vs Electric

- **General Motors** affirmed its commitment to battery-electric propulsion with the goal of “Zero emissions; Zero crashes; Zero congestion”.
- **Tesla** is pursuing the all-electric program for its “fully self-driving cars”.
- **Waymo** is using Chrysler Pacifica minivans that are plug-in hybrid electric.
- **Uber** is also opting for hybrids, having recently placed an order for plug-in hybrid Volvo XC90 SUVs.

Source: <https://www.theverge.com/2017/12/12/16748024/self-driving-electric-hybrid-ev-av-gm-ford>

Energy Management of Automated Electric Vehicles

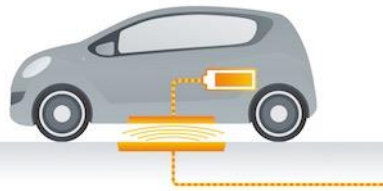


New Opportunities for Automated Electric Vehicles

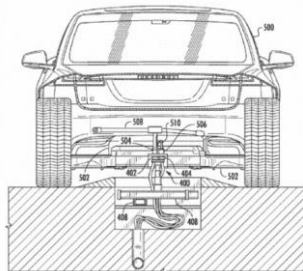
Connected Automated EVs



Automatic Charging Station



Wireless Charging

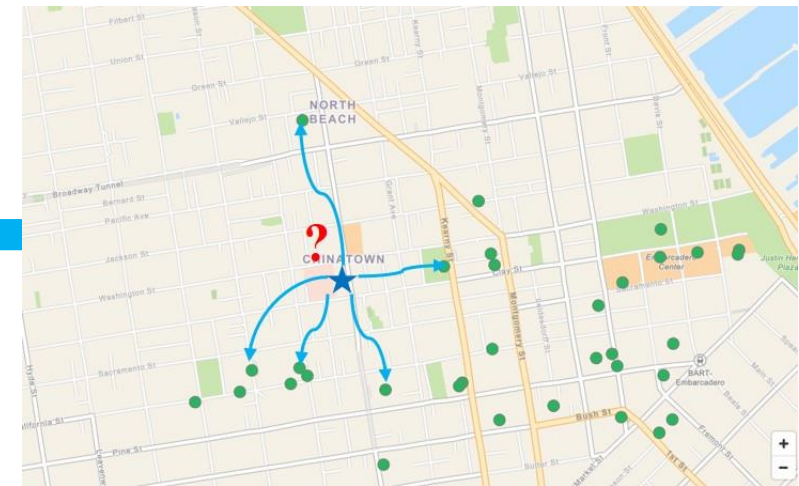


Source:
<https://patents.google.com/patent/US9527403>

Automatic Charging Decision Making

- An automatic decision making process is necessary for recharging of automated electric vehicles
- Remove the challenge of co-locating charging infrastructure with driver destinations
- Utilize real-time charging station status information

Connected Charging Station Network



Benefits

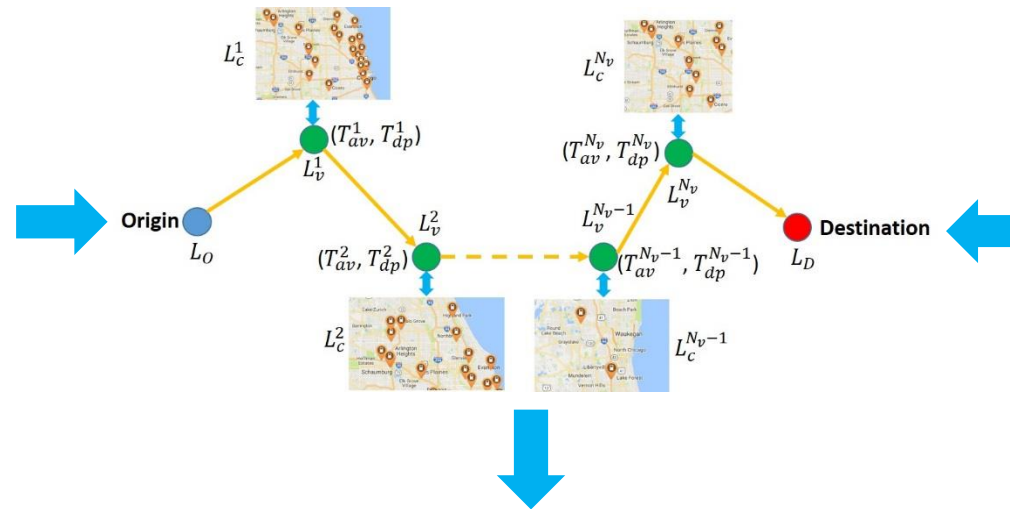
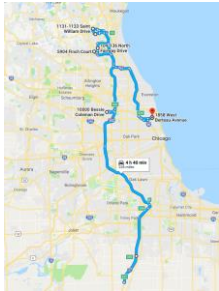
- Ensure sufficient battery energy to meet travel needs
- Minimize the energy/time/money cost of charging actions
- Facilitate the charging control and vehicle/grid integration

Source:
<http://www.ipwatchdog.com/2015/06/18/wireless-induction-charging-is-coming-to-electric-vehicles/id=58756/>

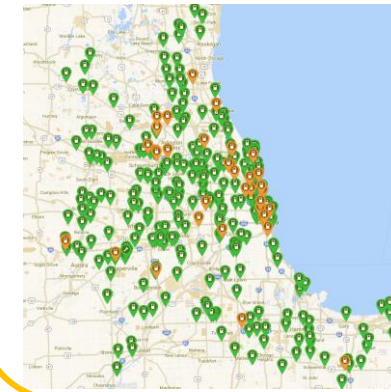
Automatic Charging Decision Making Framework

Travel/Itinerary Information

- Visited locations
- Staying time

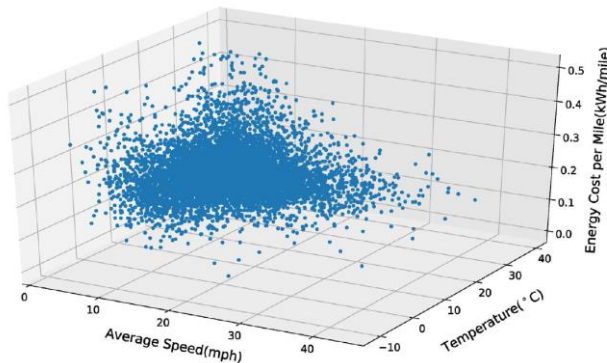


Nearby Charging Station Network



- Location
- Availability

EV Energy Consumption Model



Multi-Stage Dynamic Programming

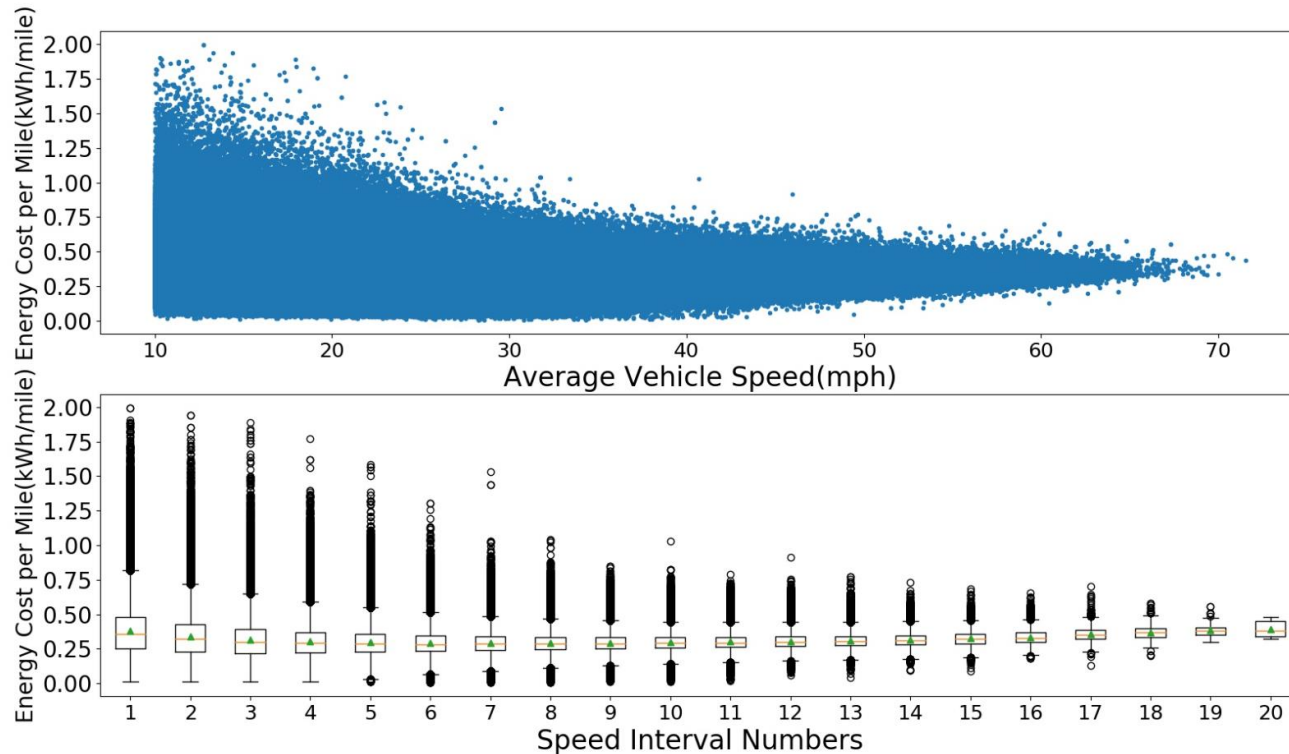
$$\begin{aligned}
 & \min_{a[1], \dots, a[N_v]} f(s[0], a[0], 0) + \sum_{k=1}^{N_v} f(s[k], a[k], k) \\
 \text{s.t.} \quad & s[0] = S_0 \\
 & s[k-1] = s[k] - \sum_{i=1}^{N_c^k} E_c^i[k] x^i[k] + E_{tc}^{(k-1,k)} + 2 \sum_{i=1}^{N_c^k} E_{cc}^i[k] x^i[k] \\
 & P_d[k] \leq s[k] \leq C_p \\
 & 0 \leq E_c^i[k] \leq E_{upr}^i[k] \\
 & x^i[k] = 0 \text{ or } 1, \text{ and } \sum_{i=1}^{N_c^k} x^i[k] \leq 1 \\
 & k = 1, \dots, N_v
 \end{aligned}$$

Optimized Charging Strategies

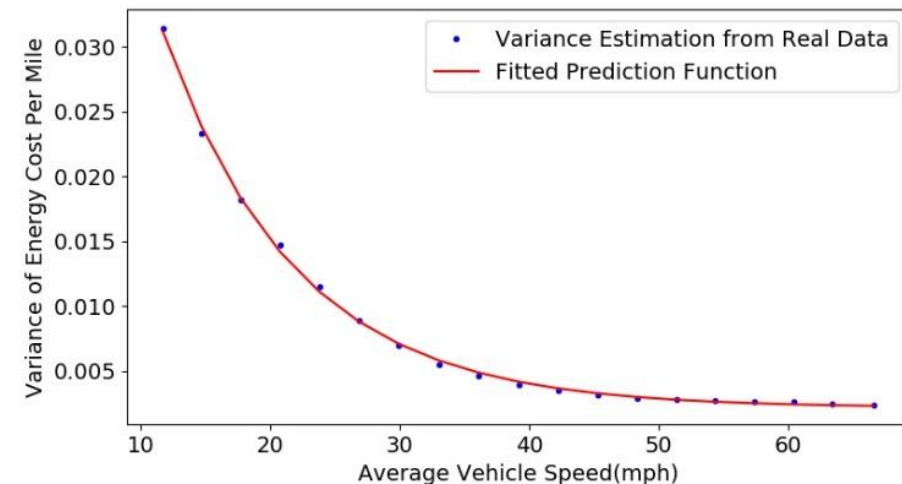
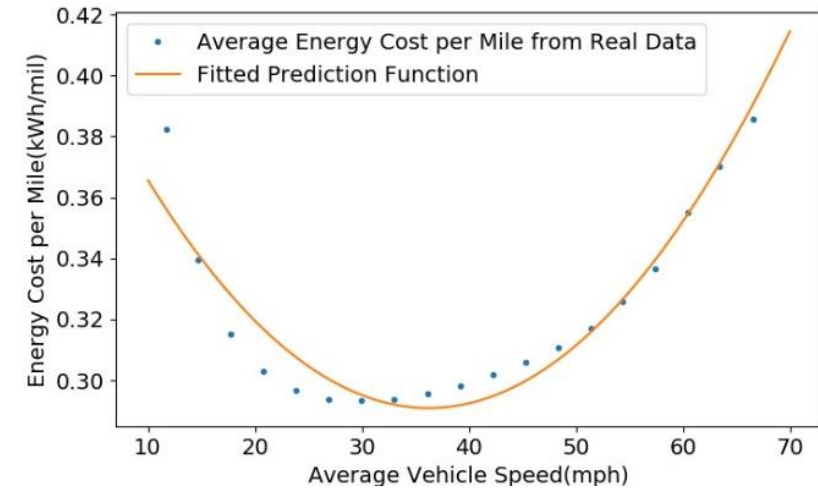
- Charging location
- Charging energy amount
- Charging time interval

Data-Driven EV Energy Consumption Modeling

- Energy cost per mile (kWh/mile) distribution

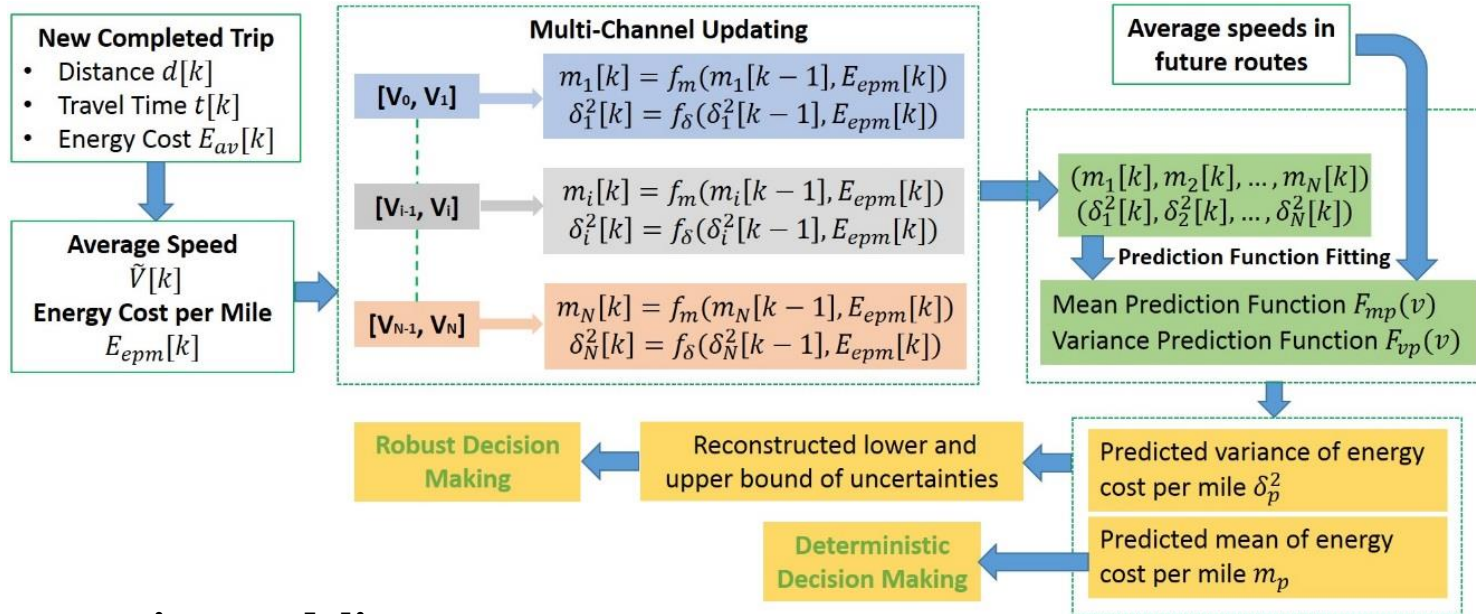


- A stochastic model for Nissan Leaf



Data-Driven EV Energy Consumption Modeling

- Multi Channels Prediction Model Construction and Real-time Update



Promising energy consumption modeling

- ✓ **Data-driven modeling** can provide a uniform format, which is independent from specific vehicle parameters, and is easy to handle real-world uncertainties.
- ✓ **Stochastic modeling** for real-world uncertainties provides the capability of decision making process to achieve robust strategies.
- ✓ **Real-time updating** is necessary to handle the dynamics of real world traffic and other environmental conditions.

Dynamic Programming for Charging Decision Making

- Multi-Stage Charging Decision Making Modeling

Deterministic (Average) Modeling

$$\begin{aligned} & \min_{a[1], \dots, a[N_v]} f(s[0], a[0], 0) + \sum_{k=1}^{N_v} f(s[k], a[k], k) \\ \text{s.t.} \quad & s[0] = S_0 \\ & s[k-1] = s[k] - \sum_{i=1}^{N_c^k} E_c^i[k] x^i[k] + E_{tc}^{(k-1, k)} + 2 \sum_{i=1}^{N_c^k} E_{cc}^i[k] x^i[k] \\ & P_d[k] \leq s[k] \leq C_p \\ & 0 \leq E_c^i[k] \leq E_{upr}^i[k] \\ & x^i[k] = 0 \text{ or } 1, \text{ and } \sum_{i=1}^{N_c^k} x^i[k] \leq 1 \\ & k = 1, \dots, N_v \end{aligned}$$

Energy Cost Prediction

- One-step prediction

$$P_d[k] = E_{tc}^{(k, k+1)}$$

- Two-step prediction

$$P_d[k] = E_{tc}^{(k \rightarrow k+1)} + E_{tc}^{(k+1, k+2)}$$

Robust Modeling

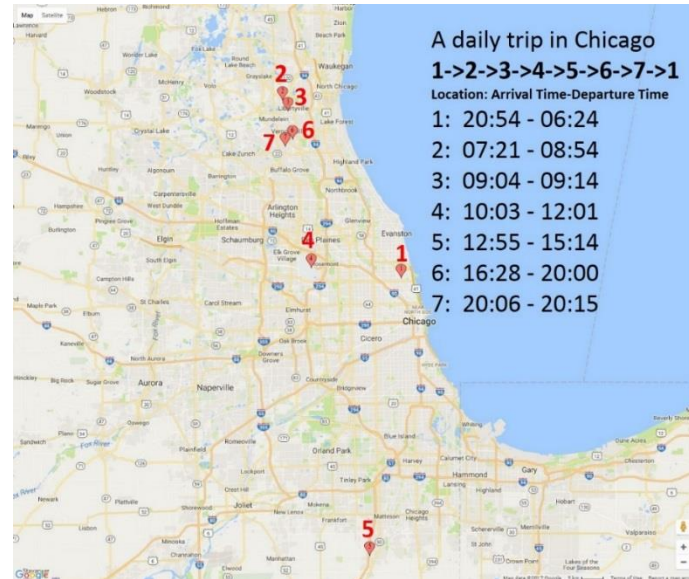
$$\begin{aligned} & \min_{a[1], \dots, a[N_v]} \max_{\substack{E_{tc}^{(k, k+1)} \in [E_{tc}^k, E_{up}^k] \\ E_{cc}^i[k] \in [E_{tc}^i[k], E_{up}^i[k]]}} f(s[0], a[0], 0) + \sum_{k=1}^{N_v} f(s[k], a[k], k) \\ \text{s.t.} \quad & s[0] = S_0 \\ & s[k-1] = s[k] - E_c[k] + E_{tc}^{(k-1 \rightarrow k)} + 2 \sum_{i=1}^{N_c^k} E_{cc}^i[k] x^i[k] \\ & P_d[k] \leq s[k] \leq C_p \\ & 0 \leq E_c^i[k] \leq E_{upr}^i[k] \\ & E_c[k] = \sum_{i=1}^{N_c^k} E_c^i[k] x^i[k] \\ & x^i[k] = 0 \text{ or } 1, \text{ and } \sum_{i=1}^{N_c^k} x^i[k] \leq 1 \\ & k = 1, \dots, N_v \end{aligned}$$

Objective Function: (Energy, Economy, etc.)

$$f(s[k], a[k], k) = \sum_{i=1}^{N_c[k]} E_c^i[k] P_r^i[k] x^i[k] + \lambda \sum_{i=1}^{N_c[k]} E_{cc}^i[k] x^i[k]$$

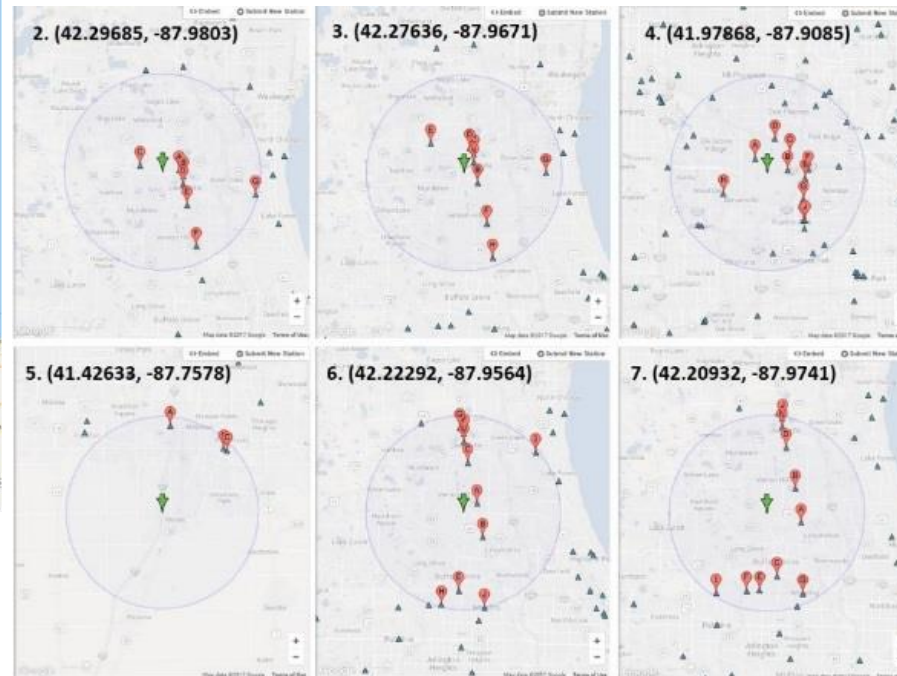
Results for Personal Automated EVs Scenario

Itinerary Information



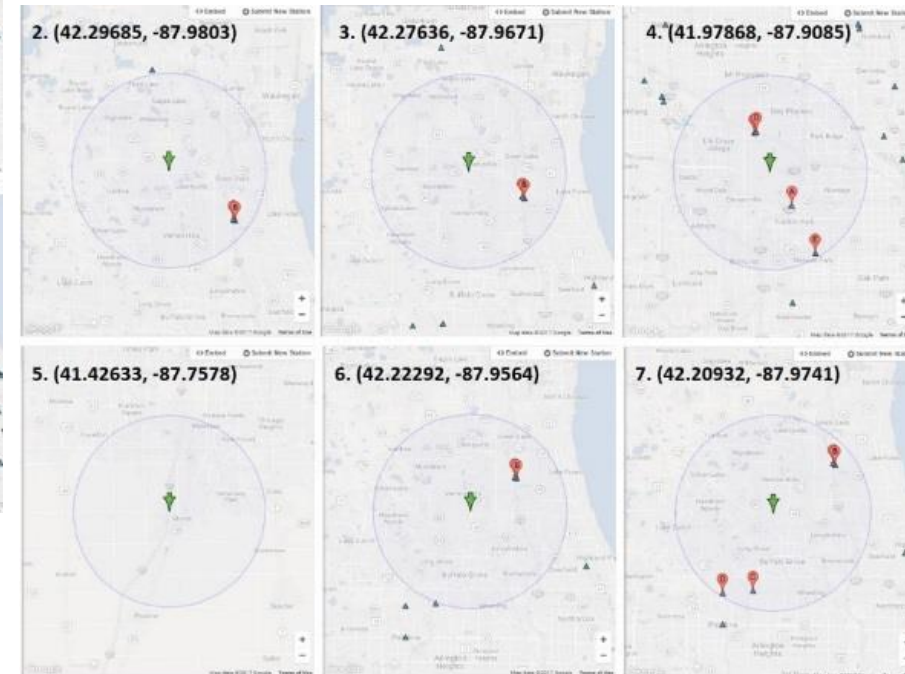
A single daily itinerary in Chicago

Level 2 Charging Stations



Nearby public charging station distribution (within 3 miles)

DC Fast Charging Stations Distribution



Charging power: 50kW

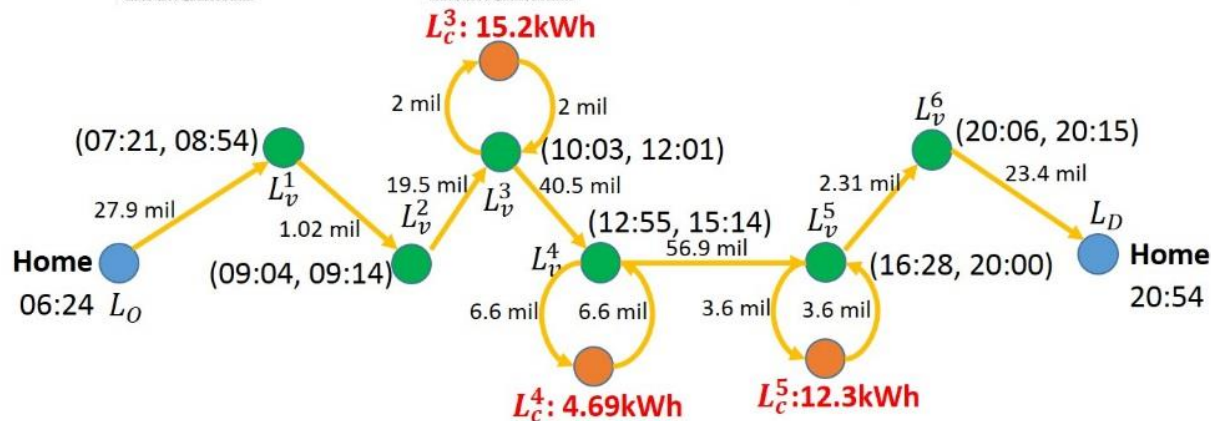
Results for Personal Automated EVs Scenario

Average Decision Making for Charging Strategies

O'Hare Airport - Short Term Parking L_c^3
 10000 Bessie Coleman Dr Chicago, IL 60666
 Access: Public - Credit card at all times
 Hours: 24 hours daily, pay lot
 Payments accepted: American Express, Discover, MasterCard, Visa
 Notes: Located in row 2 on the first floor

Hawkinson Nissan L_c^4
 5513 Miller Circle Dr Matteson, IL 60443
 Access: Public - Call ahead
 Hours: Dealership business hours

KOHL'S L_c^5
 235 N Milwaukee Ave Vernon Hills, IL 60061
 Access: Public
 Hours: 24 hours daily
 Notes: 112VERNON HILLS; EV Charging for Kohl's Customers Only - 4 hour Max

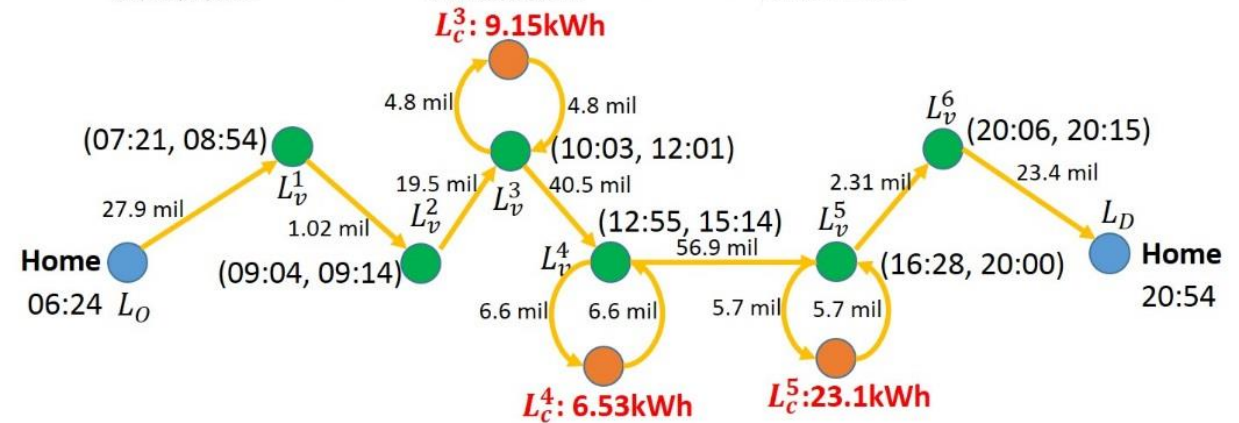


Robust Decision Making for Charging Strategies

7/11-O'HARE Oasis Out-Bound to SUB L_c^3
 4101 George Pl Schiller Park, IL 60176
 Access: Public - Card key at all times
 Hours: 24 hours daily, EVgo network subscription and key fob required

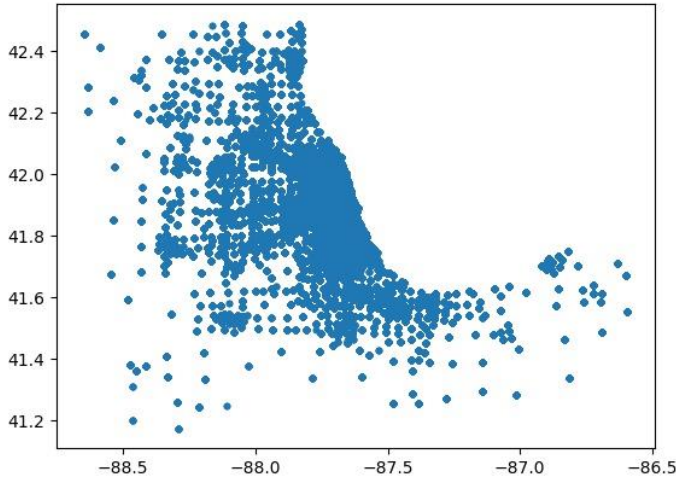
Hawkinson Nissan L_c^4
 5513 Miller Circle Dr Matteson, IL 60443
 Access: Public - Call ahead
 Hours: Dealership business hours

7/11-Lake Forest Oasis Out-Bound to Wisconsin L_c^5
 26850 E Oasis Service Rd Lake Forest, IL 60045
 Access: Public - Card key at all times
 Hours: 24 hours daily, EVgo network subscription and key fob required

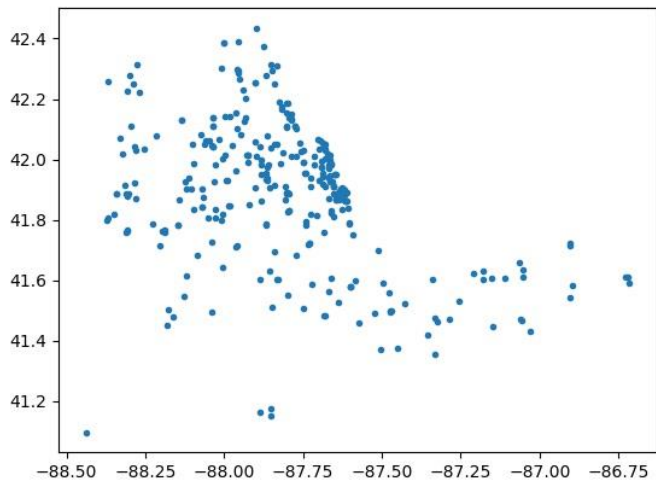


Results for Personal Automated EVs Scenario

Visited Locations

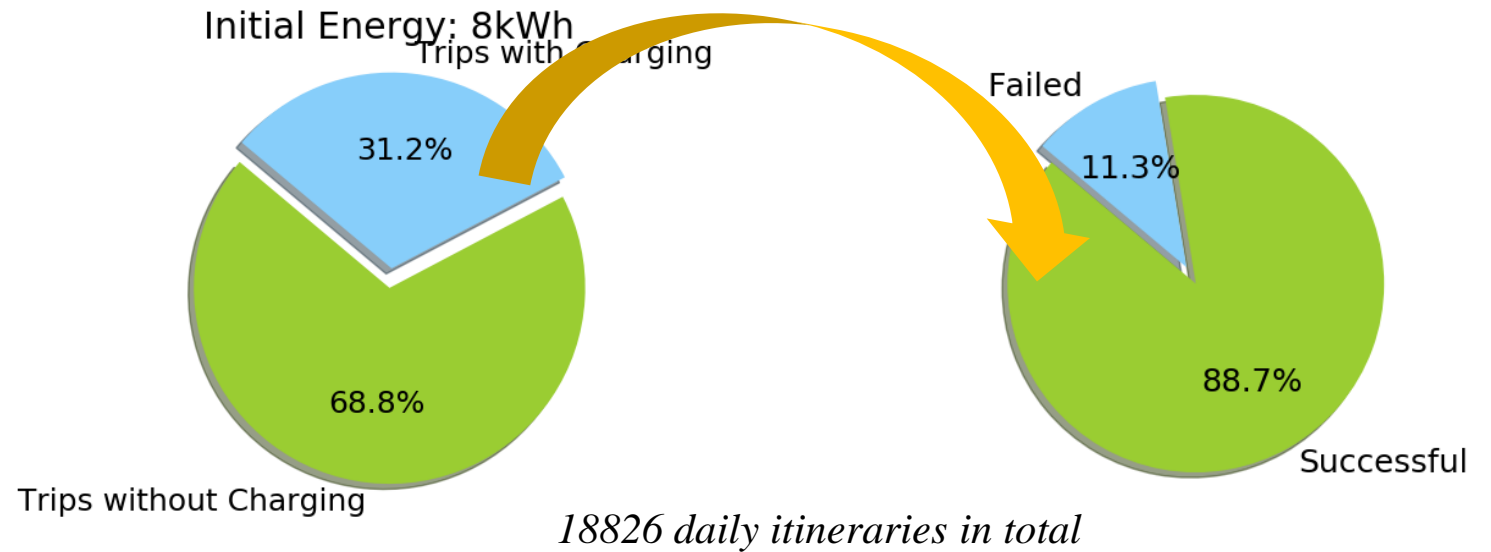


Public Charging Station Locations



Data: *Travel Tracker Survey* from the Chicago Metropolitan Agency for Planning (CMAP)

Source: <http://www.cmap.illinois.gov/data/transportation/travel-survey>



Failed: Itineraries cannot be achieved with enough energy using charging decision making algorithm.
Successful: Itineraries are achieved successfully by using charging decision making algorithm.

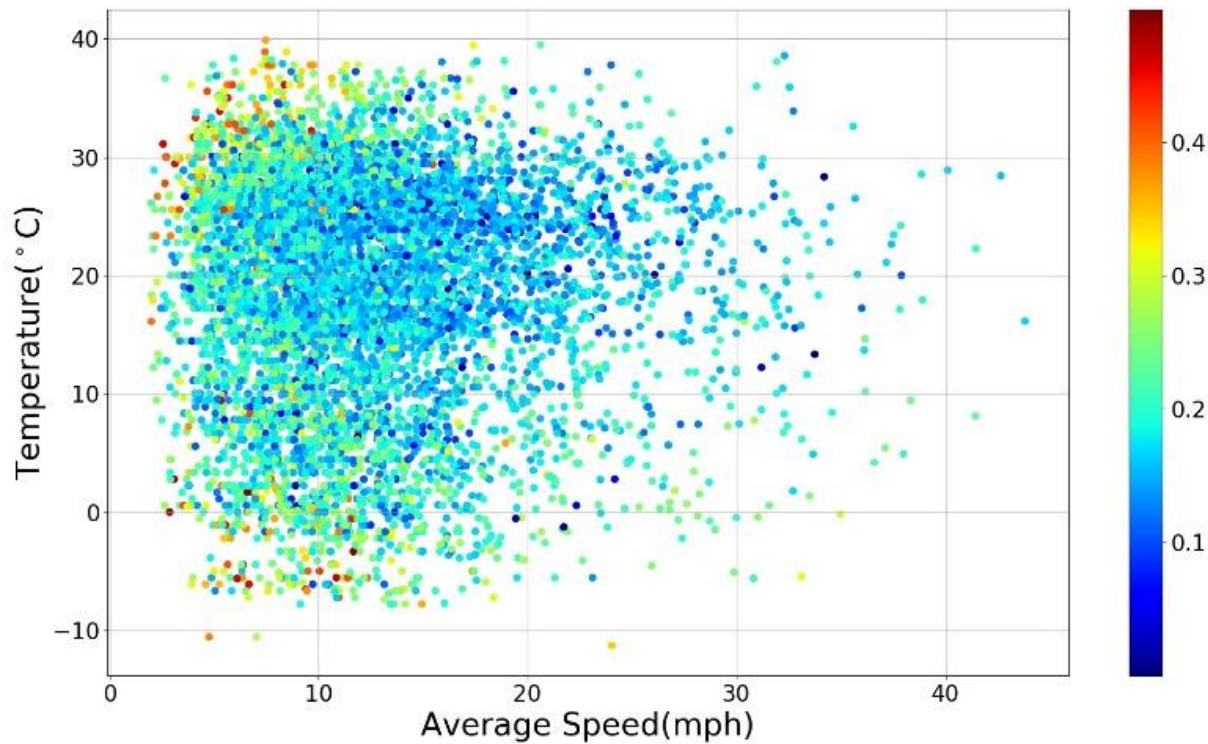
Reference: Zonggen Yi, and Matthew Shirk. "Data-driven optimal charging decision making for connected and automated electric vehicles: A personal usage scenario." *Transportation Research Part C: Emerging Technologies* 86 (2018): 37-58.

Preliminary Conclusions

- A properly designed intelligent algorithm can *achieve the recharging decision making automatically* for future automated electric vehicles.
- Automatic charging decision making works well to *reduce the range anxiety* even with current existing charging station network and can *mitigate the pain from electric vehicle charging necessity outside home*.
- More *available future trip information* during a long itinerary with several trip segments can help to achieve much better decision making overall.
- Optimized charging strategies can *minimize the monetary and energy cost of charging actions* for autonomous vehicles so as to improve the sustainability of future automated electrified transportation.

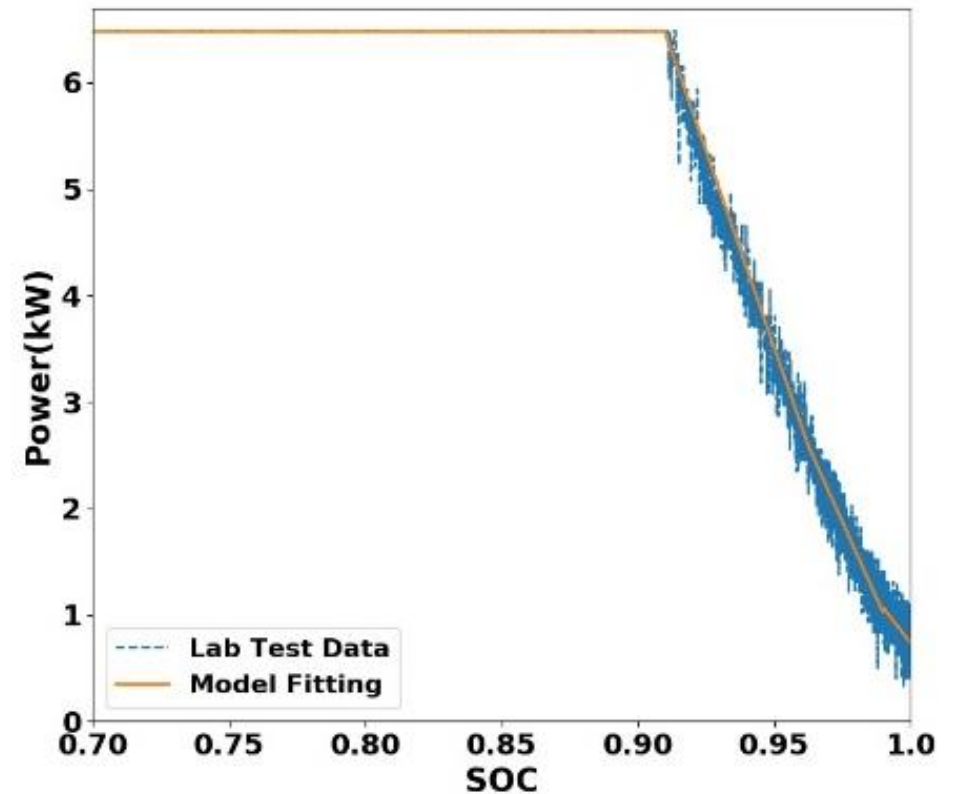
Future Work – Vehicle Level

- Energy Consumption Dynamics



Energy cost per mile of Nissan Leaf Taxi with regard to average vehicle speed and ambient temperature in New York City

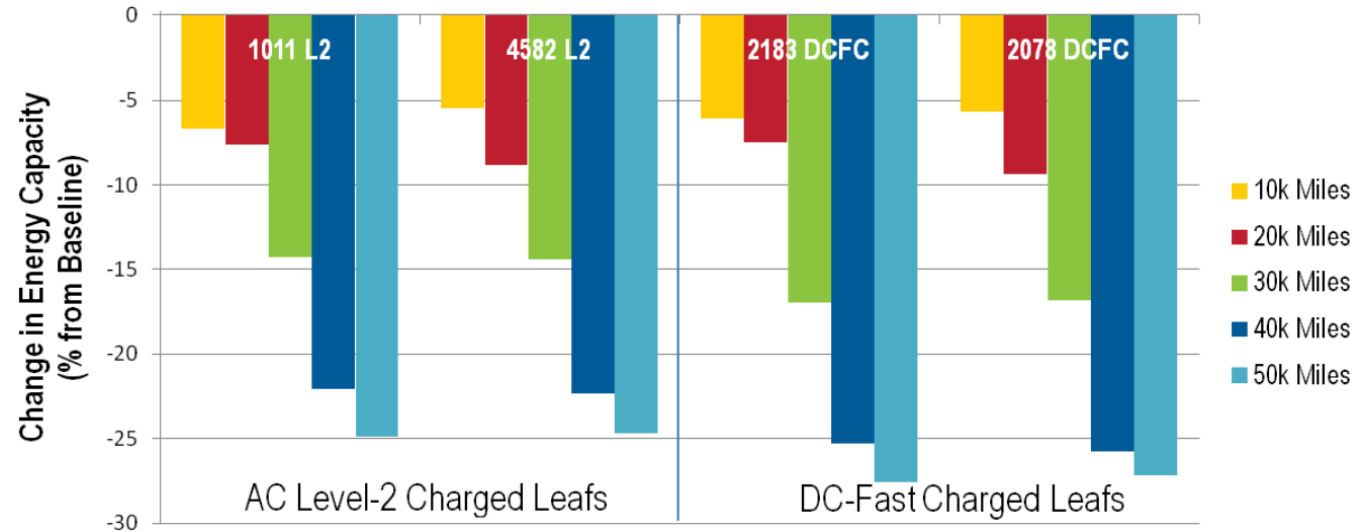
- Charging Power Dynamics



Realistic *charging power* data for a 2015 Nissan Leaf

Future Work – Vehicle Level

- Impact of High Power Charging to Battery Life



A rendering of a **350kW XFC charging station** by Electrek.

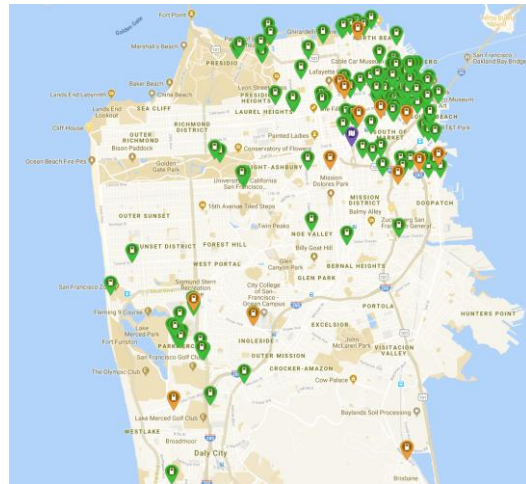
Source: <https://www.energy.gov/eere/vehicles/downloads/enabling-extreme-fast-charging-technology-gap-assessment>

Percent change in energy capacity from baseline

Source: https://www.energy.gov/sites/prod/files/2015/01/f19/dcfc_study_fs_50k.pdf

Future Work – System Level

Spatiotemporal travel demand



Charging Infrastructure

- Different charging power levels
- Dynamic utilization pattern

Preliminary research:

Zonggen Yi, John Smart, and Matthew Shirk. "Energy impact evaluation for eco-routing and charging of autonomous electric vehicle fleet: Ambient temperature consideration." *Transportation Research Part C: Emerging Technologies* 89 (2018): 344-363.

Systematic Management for Personal/Shared Automated EV Fleet

Centralized vs Decentralized

- Communication cost
- Computing cost

Eco-Routing/Eco-Driving

Co-Optimization

Recharging Decision Making