Charging Decision Making for Automated Electric Vehicles

Zonggen Yi, Ph.D.
Energy Storage and Advanced Vehicles Department
Idaho National Laboratory
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.

Energy Management of Automated Electric Vehicles

Energy Consumption
Eco-driving/Eco-routing

Energy Management of Automated EVs

Energy Recharging
Charging Decision Making
New Opportunities for Automated Electric Vehicles

Connected Automated EVs

Automatic Charging Station

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

Benefit:

- 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/
Source:
https://patents.google.com/patent/US9527403
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**

\[
\begin{align*}
\min_{a[0], \ldots, a[N_T]} & \quad f(a[0], a[0], 0) + \sum_{k=1}^{N_T} f(a[k], a[k], k) \\
\text{s.t.} & \quad a[0] = S_0 \\
& \quad a[k-1] = a[k] - \sum_{i=1}^{N} E_i^k |a[i][k] + E_i^{k-1}| + \sum_{i=1}^{N} E_i^k |a[i][k]|
\end{align*}
\]

**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

\[
\min_{a[1], \ldots, a[N_v]} \quad f(s[0], a[0], 0) + \sum_{k=1}^{N_v} f(s[k], a[k], k)
\]

s.t.
\[
s[0] = S_0
\]
\[
s[k - 1] = s[k] - \sum_{i=1}^{N_h} E_{h}^{i}[k]x^i[k] + E^{(k-1,k)}_{tc} + 2 \sum_{i=1}^{N_h} E_{cc}^{i}[k]x^i[k]
\]
\[
P_d[k] \leq s[k] \leq C_p
\]
\[
0 \leq E_{c}^{i}[k] \leq E_{upper}[k]
\]
\[
x^i[k] = 0 \text{ or } 1, \text{ and } \sum_{i=1}^{N_h} x^i[k] \leq 1
\]
\[
k = 1, \ldots, N_v
\]

#### Robust Modeling

\[
\min_{a[1], \ldots, a[N_v]} \quad \max_{E^{(k,k+1)}_{tc}, E_{cc}^{i}[k]} \quad f(s[0], a[0], 0) + \sum_{k=1}^{N_v} f(s[k], a[k], k)
\]

s.t.
\[
s[0] = S_0
\]
\[
s[k - 1] = s[k] - E_{c}[k] + E^{(k-1\rightarrow k)}_{tc} + 2 \sum_{i=1}^{N_h} E_{cc}^{i}[k]x^i[k]
\]
\[
P_d[k] \leq s[k] \leq C_p
\]
\[
0 \leq E_{c}^{i}[k] \leq E_{upper}[k]
\]
\[
E_{c}[k] = \sum_{i=1}^{N_h} E_{c}^{i}[k]x^i[k]
\]
\[
x^i[k] = 0 \text{ or } 1, \text{ and } \sum_{i=1}^{N_h} x^i[k] \leq 1
\]
\[
k = 1, \ldots, N_v
\]

#### Energy Cost Prediction

- **One-step prediction**
  \[P_d[k] = E^{(k,k+1)}_{tc}\]

- **Two-step prediction**
  \[P_d[k] = E^{(k\rightarrow k+1)}_{tc} + E^{(k+1,k+2)}_{tc}\]

#### Objective Function: (Energy, Economy, etc.)

\[
f(s[k], a[k], k) = \sum_{i=1}^{N_c} E_{c}^{i}[k]P_{r}^{i}[k]x^i[k] + \lambda \sum_{i=1}^{N_c} E_{cc}^{i}[k]x^i[k]
\]
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

Robust Decision Making for Charging Strategies
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

Initial Energy: 8kWh

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

18826 daily itineraries in total

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

- Charging Power Dynamics

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

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: