Modeling Strategies for Design and Control of Charging Stations

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EV Current Trends

1. Estimates vary substantially
2. For the US market about 7% of total by 2020-2025 and about 62% by 2050
3. Other countries: faster rates in selected countries in Asia and Europe
Sales Targets

<table>
<thead>
<tr>
<th>Country</th>
<th>Target</th>
<th>Announcement / Report Date</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>2020: 20% production</td>
<td>10 Jun 2009</td>
<td>Mitsubishi Australia</td>
</tr>
<tr>
<td>China</td>
<td>5 000 000 stock</td>
<td>March 2011</td>
<td>Electric Vehicle Initiative (EVI)</td>
</tr>
<tr>
<td>China</td>
<td>540 000 by 2015</td>
<td>8 Jul 2009</td>
<td>Pike Research</td>
</tr>
<tr>
<td>China</td>
<td>2008: 21 000 000 electric bike stock</td>
<td>27 Apr 2009</td>
<td>The Economist</td>
</tr>
<tr>
<td>Denmark</td>
<td>2020: 200 000 2020: 50 000</td>
<td></td>
<td>ENS Denmark EVI</td>
</tr>
<tr>
<td>France</td>
<td>2020: 2 000 000</td>
<td>March 2011</td>
<td>EVI</td>
</tr>
<tr>
<td>Germany</td>
<td>2020: 1 000 000</td>
<td>March 2011</td>
<td>EVI</td>
</tr>
<tr>
<td>Ireland</td>
<td>2020: 350 000</td>
<td>28 Apr 2009</td>
<td>Houses of the Oireachtas</td>
</tr>
<tr>
<td>Ireland</td>
<td>2020: 230 000 2030: 40% market share</td>
<td>1 Oct 2009</td>
<td>Electricity Supply Board (ESB)</td>
</tr>
<tr>
<td>Israel</td>
<td>2011: 40 000 EVs 2012: 40 000 to 100 000 EVs annually</td>
<td>9 Sep 2008</td>
<td>Project Better Place</td>
</tr>
<tr>
<td>Japan</td>
<td>2020: 20% market share (800 000 based on IEA estimate of 4 million)</td>
<td>March 2011</td>
<td>EVI</td>
</tr>
<tr>
<td>Netherlands</td>
<td>2015: 20 000 stock 2020: 200 000 stock</td>
<td>May 2011</td>
<td>Dutch Energy Agency</td>
</tr>
<tr>
<td>New Zealand</td>
<td>2020: 5% market share 2040: 60% market share</td>
<td>11 Oct 2007</td>
<td>Prime Minister Helen Clark</td>
</tr>
<tr>
<td>Spain</td>
<td>2020: 2 500 000</td>
<td>March 2011</td>
<td>EVI</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Country</th>
<th>Target</th>
<th>Announcement / Report Date</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sweden</td>
<td>2020: 600 000</td>
<td>March 2011</td>
<td>EVI</td>
</tr>
<tr>
<td>Switzerland</td>
<td>2020: 145 000</td>
<td>Jul 2009</td>
<td>Alpiq Consulting</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>2020: 1 200 000 stock EVs + 350 000 stock PHEVs 2030: 3 300 000 stock EVs + 7 900 000 stock PHEVs</td>
<td>Oct 2008</td>
<td>Department for Transport, “High Range” scenario</td>
</tr>
<tr>
<td>United States</td>
<td>2015: 1 000 000 PHEV stock</td>
<td>Jan 2009</td>
<td>President Barack Obama</td>
</tr>
<tr>
<td>Worldwide</td>
<td>2015: 1 700 000</td>
<td>8 Jul 2009</td>
<td>Pike Research</td>
</tr>
<tr>
<td>Worldwide</td>
<td>2020: 10% market share</td>
<td>26 Jun 2009</td>
<td>Carlos Choes, President, Renault</td>
</tr>
<tr>
<td>Europe</td>
<td>2015: 250 000 EVs</td>
<td>4 Jul 2008</td>
<td>Frost &amp; Sullivan</td>
</tr>
<tr>
<td>Europe</td>
<td>2015: 480 000 EVs</td>
<td>8 May 2009</td>
<td>Frost &amp; Sullivan</td>
</tr>
<tr>
<td>Nordic countries</td>
<td>2020: 1 300 000</td>
<td>May 2009</td>
<td>Nordic Energy Perspective</td>
</tr>
</tbody>
</table>

Source: Individual Country Roadmaps and Announced Targets, as listed in the references.

Figure 6: National EV/PHEV sales targets if national target year growth rates extend to 2020
Key Drivers of Increased Penetration Rates

1. Environmental concerns
2. Tax and other incentives
3. Increased availability of EV models
dozens of models came to the market place in last 18 months, from small compacts to large sedans
4. Improvements in battery technology \(\Rightarrow\) decreased cost
Battery technologies

Fig. 1. Battery potential and PHEV “Goals” (Ragone plots) [18].
Operation Cost

Total Energy Cost (Gasoline plus Electricity) per 100 Miles

- **Ford Expedition**: $31.90
- **Toyota Sienna**: $22.27
- **Toyota Corolla**: $14.68
- **Ford Escape Hybrid**: $14.05
- **Toyota Prius Hybrid**: $9.34
- **Ford Escape Plug-in Hybrid**: $11.26
- **Toyota Prius Plug-in Hybrid**: $6.90
Characteristics of Electric Vehicles

<table>
<thead>
<tr>
<th>Type</th>
<th>Tesla Roadster</th>
<th>Nissan Leaf</th>
<th>GM Chevy Volt</th>
<th>Toyota Plug-in Prius</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electric Range</td>
<td>245 miles</td>
<td>100 miles</td>
<td>35 miles</td>
<td>15 miles</td>
</tr>
<tr>
<td>Battery Size</td>
<td>53 kWh</td>
<td>24 kWh</td>
<td>16 kWh</td>
<td>4.4 kWh</td>
</tr>
<tr>
<td>Onboard Charger</td>
<td>9.6 kW</td>
<td>3.3 kW</td>
<td>1.44 kW</td>
<td>1.44 kW</td>
</tr>
<tr>
<td>Quick Charger</td>
<td>16.8 kW</td>
<td>60 kW</td>
<td>3.3 kW</td>
<td>3.3 kW</td>
</tr>
<tr>
<td>Charging Time</td>
<td>6 hours (onboard)</td>
<td>6 hours (onboard)</td>
<td>10 hours (onboard)</td>
<td>3 hours (onboard)</td>
</tr>
<tr>
<td></td>
<td>3.5 hours (quick)</td>
<td>0.5 hours (quick)</td>
<td>4 hours (quick)</td>
<td>1.5 hours (quick)</td>
</tr>
<tr>
<td>Price (MSRP)</td>
<td>$109,000</td>
<td>$35,200</td>
<td>$40,280</td>
<td>$32,000</td>
</tr>
</tbody>
</table>

Challenges posed by EVs

1 Consumer:
   1. Long charging times
   2. Lack of adequate charging station infrastructure $\implies$ range anxiety

2 Utilities:
   1. Large stochastic, mobile loads
   2. Added capacity required
Charging Levels and Expected Times

**TABLE I**

**U.S. STANDARD ELECTRIC VEHICLE CHARGING LEVEL**

<table>
<thead>
<tr>
<th>Level</th>
<th>Voltage (VAC)</th>
<th>Current (Amps)</th>
<th>Power (kVA)</th>
<th>Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1</td>
<td>120</td>
<td>12</td>
<td>1.44</td>
<td>Single</td>
</tr>
<tr>
<td>Level 2</td>
<td>208/240</td>
<td>32</td>
<td>6.7/7.7</td>
<td>Single</td>
</tr>
<tr>
<td>Level 3</td>
<td>240</td>
<td>70</td>
<td>16.8</td>
<td>Three</td>
</tr>
</tbody>
</table>

**TABLE II**

**TYPICAL EV CHARGING TIME**

<table>
<thead>
<tr>
<th>EV Configuration</th>
<th>Battery Size (kWh)</th>
<th>120 V and 12 Amps</th>
<th>240 V and 32 Amps</th>
<th>480 V and 100 Amps</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHEV-10</td>
<td>4</td>
<td>3h 5m</td>
<td>35m</td>
<td>n/a</td>
</tr>
<tr>
<td>PHEV-20</td>
<td>8</td>
<td>6h 10m</td>
<td>1h 10m</td>
<td>n/a</td>
</tr>
<tr>
<td>PHEV-40</td>
<td>16</td>
<td>12h 20m</td>
<td>2h 20m</td>
<td>63m</td>
</tr>
<tr>
<td>BEV</td>
<td>24</td>
<td>18h 30m</td>
<td>3h 30m</td>
<td>1h 34m</td>
</tr>
<tr>
<td>PHEV Bus</td>
<td>50</td>
<td>n/a</td>
<td>5h 50m</td>
<td>3h 17m</td>
</tr>
</tbody>
</table>

Source: Su et al. (2012), IEEE Transactions on Industrial Informatics
The level 1 charging load is about 1.5 and level 2 charging load is about 5.5 times of the average base household load. If every household owns just one PEV in the near future, the peak demand of the grid load from charging the PEVs can increase the peak load by a factor between 2.5 to 6.5 times of the current peak load. This peak load would not only increase the peak load that a distribution network (regional or local) draws from the transmission grid, but also cause stress on its transmission lines and transformers.

Source: Ghavami et al. (2013), Decentralized Charging of Plug-In Electric Vehicles with Distribution Feeder Overload Control, on arXiv
Extensive Work on the Subject

Key Theme:

Manage aggregate loads to:

1. mitigate generation scheduling problems
2. avoid overloads of the distribution network
3. support increased penetration of EVs
Prior Work

1. Work focused on designing novel demand response schemes
2. Tools used: game based decentralized control, queuing models, incentive designs
3. Many papers focused on overnight charging of EVs subject to deadlines
Designing and Managing Charging Infrastructure

Challenges for Charging Stations

1. Varying arrival-departure schedule and demand
2. Utilities often offer time-varying time of day pricing schemes for electricity
3. The charging infrastructure is an expensive and limited resource and needs to be managed efficiently
Recent Trends in Charging Station Infrastructure

Tesla’s projected Charging Station Network
Increased Availability of Charging Stations
**New Initiatives**

**ABB to build world’s largest nationwide network of EV fast-charging stations in the Netherlands**

ABB wins contract for nationwide electric vehicle fast-charging infrastructure in the Netherlands bringing a charging station within 50 kilometers of all 16.7 million inhabitants.

Zurich, Switzerland, July 8, 2013 – ABB, the leading power and automation technology group, announced today that it has been selected by Fastned to supply chargers to more than 200 electric vehicle fast-charging stations in the Netherlands, bringing an EV fast charger within 50 kilometers of all of the country’s 16.7 million inhabitants.

Each of the more than 200 Fastned stations along Dutch highways will be equipped with several multi-standards fast chargers, such as the 50 kilowatt (kW) Terra S2 and Terra S3 models, capable of charging electric vehicles in 15-30 minutes. The first ABB Terra fast chargers are due to be delivered in September 2013. Construction of the Fastned stations, which will have solar canopies, is expected to be completed by 2015.

To date, the Netherlands is the most populous country to roll out a nationwide fast-charging network. Fast-chargers will be located a maximum of 50 kilometers apart along all highways, and because of ABB’s multi-standard design, the network will be capable of serving EVs offered by all major car brands from Europe, Asia and the USA. ABB’s open standards-based cloud connectivity solution allows Fastned to create a user-friendly payment and access service for all drivers.
Charging Station Design

Key aspects:

1. Small (current gas station) to large (parking lot) size
2. Incorporation of local storage devices
Small scale stations

1. Station draws constant power from the grid (better pricing with long term contracts and ensures grid reliability)
2. Local energy storage system (ESS) is employed to alleviate demand spikes
3. ESS recharged when slack capacity available
4. Station’s operations modeled by a loss system
5. QoS metric used: long-term blocking probability of incoming customers
1. EVs arrive according to a Poisson process of rate $\lambda$.
2. Receive service at rate $\mu$.
3. System operations quantized by number of charging slots $S$ from the grid and $R$ from the ESS.
4. ESS recharged at rate $\nu$ (that depends on its characteristics).
Illustration of performance for different system parameters
Q: How does the underlying ESS technology affect the system performance?

ESS charging depends on two key parameters: energy storage efficiency $\eta_{eff}$ and power rating $S_{PR}$. 

![Graph showing discharge time and recharge time for different technologies]

<table>
<thead>
<tr>
<th>Technology</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Battery</td>
<td>60%-80%</td>
</tr>
<tr>
<td>Flywheel</td>
<td>93%</td>
</tr>
<tr>
<td>Sup-capacitors</td>
<td>95%</td>
</tr>
<tr>
<td>Hydrogen Fuel Cell</td>
<td>59%</td>
</tr>
</tbody>
</table>
Comparison of different charging strategies

1. Strategy 1: Charge EVs from the grid first, and employ storage unit as backup
2. Strategy 2: Charge EVs from the local energy storage unit, and use the grid as backup

For *Slow* energy storage technologies use the charge from the grid first. Otherwise employ Charge from the storage first.
Sizing the Charging Station

The stochastic model employed provides insight into QoS performance, but not an explicit scheme for sizing.

For that purpose, introduce a revenue-cost model:

1. Station operator receives revenue for EVs served and pays a cost for rejecting customers.
2. In addition, fixed deployment costs (physical space occupied, technology deployed, etc.) are included.

\[
P = \sum_{s \in \mathcal{S}^{(1)}} R_s i(s) \pi(s) + \sum_{s \in \mathcal{S}^{(2)}} R_s i(s) \pi(s) - (C_0 + RC_1 + vC_2) - \sum_{s \in \mathcal{S}^{(1)}} C_b i(s) \pi(s)
\]
### Modeling Considerations

1. Large number of charging slots $N$
2. Each slot can be in an ON/OFF state
3. Assuming Poisson arrivals and exponential service rates, we have that probability a slot is on is given by $\frac{\lambda}{(\lambda + \mu)}$.
4. Demand $\sum_{i=1}^{n} D_i p < P$, where $P$ is total power available
Objective

Determine the amount of effective power so that a large portion of customers is served.

Using concepts from large deviations (Chernoff’s bound), we can determine a rate function $A(r) > 0$, such that

$$P\left( \sum_{i=1}^{N} D_i > Nr \right) < \exp(-NA(r))$$
Left panel: illustration of rate function; Right panel: Trade-off between performance gains and number of stations ($\delta = NA(r)$)
Networks of Charging Stations

A network of charging stations has EVs and stations at many locations, and possibly with different technologies.

Idea of system: an EV that wants to recharge sends signal to nearby stations, gets responses, and decides where to go (automatically or with user input).
Networks of Charging Stations

A network of charging stations has EVs and stations at many locations, and possibly with different technologies.

Idea of system: an EV that wants to recharge sends signal to nearby stations, gets responses, and decides where to go (automatically or with user input).
Assume EVs have preferences between charging stations, i.e. costs $c_i(j)$ ($i =$ vehicle type, $j =$ station)

Basic linear program:

$$\text{minimize } \sum \lambda_{ij} c_i(j)$$
$$\text{s.t. } \sum_{j} \lambda_{ij} = \lambda_{i}$$
$$\sum_{i} \frac{\lambda_{ij}}{\mu_{ij}} \leq N_{j}$$
$$\text{over } \lambda_{ij} \geq 0$$

where $N_{j}$ is the number of charging slots at station $j$, $\lambda_{i}$ the arrival rate of vehicles of type $i$, $\mu_{ij}$ the service rate of a vehicle of type $i$ at a station of type $j$, and suppose EVs of type $i$ are routed to station $j$ at rate $\lambda_{ij}$
On-line solution: Greedy Primal-Dual algorithm

1. Each station keeps a virtual queue $Q_j$, a charge per unit time spent at the station.

2. When an EV of type $i$ broadcasts a request for charging at time $t$, all stations in its neighborhood reply with values of $\beta Q_j(t)/\mu_{ij}$, and the EV picks station $j^*$ that minimizes the sum $c_i(j) + \beta Q_j(t)/\mu_{ij}$ of its intrinsic cost and the reply.

3. The station that receives the EV increments $Q_j \mapsto Q_j + \mu_{ij}^{-1}$.

4. All stations decrement their virtual queues at rate $N_j$ (number of charging slots).
- Nice features: on-line, adapts to (slowly)-changing arrival rates, obtain a diffusion approximation once the algorithm reaches steady-state.
- Less nice features: for finite $N$, have more queueing than necessary.
  - The latter is an unwelcome feature in itself
  - Further, EV drivers are unlikely to follow a recommendation of “join this queue when adjacent station has no queue”.
- Want some form of load-balancing.
Two approaches to load-balancing:

- **Load-balancing linear program and corresponding GPD algorithm**
  - Need to decide the relative size of overload penalty and the costs $c_i(j)$
  - Can do “partial load-balancing” where overload at different stations is penalized differently
  - Slow to absorb fluctuations – queue sizes / loads will be equal on large scale

- Can do faster load-balancing on the tree of basic activities
Overview of basic activities:

\[
\begin{align*}
\text{minimize} & \quad \sum \lambda_{ij} c_i(j) \\
\text{s.t.} & \quad \sum_j \lambda_{ij} = \lambda_i \quad \rightarrow \nu_i \\
& \quad \sum_i \frac{\lambda_{ij}}{\mu_{ij}} \leq N_j \quad \rightarrow q_j \\
& \quad \text{over } \lambda_{ij} \geq 0
\end{align*}
\]

The dual variables satisfy

\[
\nu_i \leq c_i(j) + \frac{q_j}{\mu_{ij}} \quad \forall i, j
\]

with equality if and only if \( \lambda_{ij} > 0 \). These \((ij)\) are the basic activities.
In general, the set of basic activities is acyclic (as an undirected graph). Freest-Charger Shortest-Queue load balancing along the tree:

- If there are available slots at some charging station *in the basic activity tree*, join the station with lowest load.
- If not, join the station with shortest queue.
Pros:
- Balances loads and queue sizes
- When it works, results in small and equal queues (simulation results)
- Allows flexibility in placing excess capacity
  - Capacity is pooled across a connected component of basic activity tree
- Should be faster at reacting to changes in arrival pattern

Cons:
- May be unstable, particularly in the regime of large connected components
  - (Not much of an issue for small systems, or for service rates depending on station technology)
- Need to recalculate the basic activity tree if arrival pattern changes significantly
  - (Can run a GPD-like algorithm in the background)
- Challenging on how to incorporate costs explicitly
1. Arrival processes $A_{ij}(t)$, and Service Processes $S_{ij}(t)$

2. All of them satisfy functional LLNs uniformly on compact sets and CLTs

\[
\frac{1}{r} A_i(rt) \xrightarrow{r \to \infty} \lambda_i t, \quad \frac{1}{r} S_{ij}(rt) \xrightarrow{r \to \infty} \mu_{ij} t, \quad \text{as } r \to \infty
\]

\[
\frac{1}{\sqrt{r}} (A_i(rt) - \lambda_i rt) \xrightarrow{r \to \infty} W_i(t), \quad \frac{1}{\sqrt{r}} (S_{ij}(rt) - \mu_{ij} rt) \xrightarrow{r \to \infty} W_{ij}(t),
\]

as $r \to \infty$,
Result 1

Define the scaled variables $\hat{q}_j^r(t) = r^{-1/2} \left( Q_j^r(t) - (\beta^r)^{-1} q_j^* \right)$.

Consider the sequence of systems indexed by $r$ as above, where system $r$ is running the GPD algorithm with $\beta^r = r^{-3/4}$. Suppose the arrival and service completion processes are Poisson, and the parameters $\mu_{ij}$ are rational, so that the virtual queueing system can be modeled by a countable state-space Markov process. For each $r$, consider the associated stationary version of the process, and let $\hat{q}_j^r$ be the stationary version of $\hat{q}_j^r(t)$. Then $(\hat{q}_j^r)_j \rightarrow 0 \in \mathbb{R}^J$.

Remark: Poisson process assumptions made to avoid technicalities on process convergence.
Result 2

Consider the sequence of systems indexed by $r$ as above, and suppose that $(\hat{q}_j^r(0))_{j} \to 0 \in \mathbb{R}^J$. Suppose further that the system is critically loaded. Then $\hat{a}_{ij}^r(\cdot) \implies H(W)$, where $W$ is the Brownian motion identified in the functional CLT assumption, and $H$ is a linear mapping defined below. Thus, $H(W)$ is also a Brownian motion, but with correlated components.

The linear map $H : \mathbb{R}^I \to \mathbb{R}^{I+J-1}$ is defined as follows. For a vector $\nu = (v_1, \cdots, v_I) \in \mathbb{R}^I$, the image $w = H(\nu)$ with coordinates indexed by basic activities $(ij)$ satisfies

\[
\sum_{j} w_{ij} = v_i, \quad \forall i;
\]

\[
\sum_{j} \frac{\mu_{i'j}}{\mu_{ij}} w_{i'j} = \sum_{j} \frac{\mu_{i''j'}}{\mu_{ij'}} w_{i''j'}, \quad \forall i, (ij), (ij').
\]
Remarks:

1. First result shows that in steady-state, the virtual queues will be large and proportional to the optimal dual variables $q^*_j$, namely $Q^r_j \approx (\beta^r)^{-1} q^*_j$.

2. Second result indicates that after the GPD algorithm has converged, it results in a good routing pattern.

3. The choice of $\beta^r = r^{-3/4}$ in the above two results is not essential; we could choose $\beta = f(r)$ for any function $f(r)$ satisfying $rf(r) \to \infty$ and $r^{1/2}f(r) \to 0$. Choosing larger values of $\beta$ will lead to faster convergence to equilibrium, but lower precision for finite values of $r$. 
We get to choose where charging infrastructure will be built. What can we say about it?

EV profiling analytics come into play.

Want large connected components in the basic activity tree, because these mean more resource pooling and more flexibility in where excess capacity goes.

Practical challenge: How do we construct the infrastructure so that this happens?
Another form of resource pooling arises from charging station equipped with energy storage devices (ESS)

Question: can we run the system so that these look like a single battery pool?
Role of Communications

1. **Mobile EVs** need to locate and reserve a charging station through information distributed to them from wireless communications.

2. **Charging station operators** need to control and coordinate EV chargings as well as monitor station usage.
Some Questions

1. What are the most appropriate technologies: 3/4G, WiMax, etc.
2. How do various models behave under degradation in communications
Role of Analytics

1. Profiling studies for capacity planning
2. Fast monitoring and forecasting schemes for demand response solutions
Towards the Whole Picture

Fig. 1. Integrating three domains affected by electric mobility for effective analysis: power systems, transportation systems, and vehicle technology.

Fig. 2. The integrated method comprising the vehicle technology assessment model (VTAM), the multiagent transportation simulation (MATSim), and the PEV management and power system simulation (PMPSS).

Figure from Galus et al. (2012), IEEE Trans on SmartGrid