
Wencong Su, Ph.D.
Assistant Professor
Department of Electrical and Computer Engineering
University of Michigan-Dearborn
E-mail: wencong@umich.edu
Web: www.SuWencong.com
Transportation sector consumes 1/3 of total energy in U.S.A.

Current U.S. vehicle fleet = ~250 millions vehicles

Getting charged up about a gasoline-free future!

Plug-in Electric Vehicles are coming!!!

Projected Plug-in Vehicle Market Share

- 1 Million PHEVs/PEVs on the road by 2015
- 425,000 PHEVs/PEVs will be sold in 2015
- 2.5% of all new vehicle sales in 2015
- 62% of the entire US vehicle fleet by 2050

10% market share of PHEVs/PEVs
~10kW charging level

250 million vehicles
X 10%
X 10kW
250 GW
1,000 GW (total U.S. installed generation capacity)
Study effects of the aggregate behavior of PEV charging loads on power grids

Simulate the aggregate peak demand under various charging scenarios

Estimate the aggregate PEV traffic demand, driving behavior, and traffic pattern

(1) When would PEVs (time) start to be recharged?
(2) How much electrical energy (kWh) is needed to charge PEVs?
(3) What level of charge (kW) is needed at each time step?
Motivation:

- Plug-and-Play feature
- PEV charging load profile is highly uncertain and unpredictable
- The majority of existing work is based on a complete set of predefined data (e.g., initial battery State-of-Charge, when to start/stop charging, and where to charge)
- Unfortunately, the perfect PEV charging load forecasting data over the entire energy scheduling horizon (e.g., next 24 h) is generally not available in real-world power system operations.
- Self-confined and small-scale distribution system or Microgrid is sensitive to even a small amount of uncertainty.


**Objective:**

- Achieve the optimal power dispatch for Microgrid under uncertainties
- Minimize the operational cost with high-penetration of PEV charging loads
- Keep the real-time power balance

**Challenge and Opportunity:**

- Lack of historical PEV charging data
- Most of the existing PEV charging load estimation is not accurate (e.g., National Household Travel Survey 2009)
- Smart meters can monitor the electric energy consumption at every single PEV charging stations in real time.
- In general, the near-term forecast is much more accurate.
Model Predictive Control (MPC) is an advanced method for process control, which has been widely used in many applications [1-2].

MPC is a **receding horizon**-based approach

1. At time $k$, solve an open-loop optimal control problem over the receding $N$ time steps considering the current state $x(k)$ and future constraints.

$$\begin{align*}
\hat{x}(k) &= x(k) \\
\text{Min} \sum_{i=k}^{k+N-1} F(\hat{x}(i), \hat{u}(i)) & \quad \hat{x}(i+1) = A\hat{x}(i) + B\hat{u}(i) \quad i = k, k + 1, ..., k + N - 1 \\
g(\hat{x}(i), \hat{u}(i)) & \leq 0 \quad i = k, k + 1, ..., k + N - 1
\end{align*}$$

$$U^* = \{\hat{u}(k)^*, \hat{u}(k+1)^*, ..., \hat{u}(k+N-1)^*\}$$

2. Apply the first step in the optimal control sequence $u(k) = \hat{u}(k)^*$

3. Repeat the procedure at time $(k+1)$ using the current state $x(k+1)$.


Look-ahead power dispatch

- A multi-step optimization problem
- Consider the inter-temporal constraints and benefits

One-step solution at the current time \( t \)

Min \( F(t) = \sum_j c_j(P_j(t)) + \sum_k c_k(P_k(t)) + c_{grid}(P_{grid}(t)) + \rho \times (D_L(t) - D_{base}(t)) \)

Subject to

\[ \sum_m P_m(t) + \sum_n P_n(t) + P_j(t) + P_{grid}(t) + P_k(t) = P_{loss}(t) + D_L(t) + D_{PEV}(t) \]

\[ P_{j,\text{min}} \leq P_j(t) \leq P_{j,\text{max}} \quad P_{k,\text{min}} \leq P_k(t) \leq P_{k,\text{max}} \quad SoC_{k,\text{min}} \leq SoC_k(t) \leq SoC_{k,\text{max}} \]

\[ \Delta P_{j,\text{min}} \leq P_j(t) - P_j(t-1) \leq \Delta P_{j,\text{max}} \quad \Delta P_{k,\text{min}} \leq P_k(t) - P_k(t-1) \leq \Delta P_{k,\text{max}} \]

Two-step solution at the current time \( t \)

Min \([F(t) + F(t+1)]\)

\[ F(t) = \sum_j c_j(P_j(t)) + \sum_k c_k(P_k(t)) + c_{grid}(P_{grid}(t)) + \rho \times (D_L(t) - D_{base}(t)) \]

Subject to

\[ \sum_m P_m(t) + \sum_n P_n(t) + P_j(t) + P_{grid}(t) + P_k(t) = P_{loss}(t) + D_L(t) + D_{PEV}(t) \]

\[ \sum_m P_m(t+1) + \sum_n P_n(t+1) + P_j(t+1) + P_{grid}(t+1) + P_k(t+1) = P_{loss}(t+1) + D_L(t+1) + D_{PEV}(t+1) \]

\[ P_{j,\text{min}} \leq P_j(t) \leq P_{j,\text{max}} \quad P_{k,\text{min}} \leq P_k(t) \leq P_{k,\text{max}} \quad SoC_{k,\text{min}} \leq SoC_k(t) \leq SoC_{k,\text{max}} \]

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\[ \Delta P_{j,\text{min}} \leq P_j(t+1) - P_j(t) \leq \Delta P_{j,\text{max}} \quad \Delta P_{k,\text{min}} \leq P_k(t+1) - P_k(t) \leq \Delta P_{k,\text{max}} \]
Model Predictive Control-based Power Dispatch

1. Monitor the EV charger information at time $i$
   \[ x(i) = [SOC, TR, Cap, h] \]

2. Use the real measurement as initial state \( \hat{x}(i) = x(i) \)

3. Update the predictive model
   \[
   DEV_{MPC}^H(t) = DEV_{MPC}^{H-h}(t) + DEV^h(t). \quad h \leq H, \ t = i+1, \ldots, i+N-1
   \]
   \[
   DEV^h = f(h, SOC, Cap, T_{in}, T_{out}).
   \]
   \[
   DEV^H = f(H, SOC, Cap, T_{in}, T_{out}).
   \]

4. Solve a deterministic optimization problem based on look-ahead finite-horizon prediction (next $N$ hours)
   Minimize
   \[
   F = \sum_i \sum_j c_j(P_j(t)) + \sum_i \sum_k c_k(P_k(t)) + \sum_t c_{grid}(P_{grid}(t)). \quad t = i,i+1,\ldots,i+N-1
   \]
   \[
   U^* = \{u(i), u(i+1), \ldots, u(i+N-1)\} \quad u(i) = \{P_j(i), P_k(i)\}.
   \]

5. Only perform the first step of the open-loop optimal control sequences $u(i)$
The MPC-based approach effectively compensates the PEV charging uncertainty by incorporating the most updated real-time information at each time step.

\[
\text{Index}_F = \frac{\overline{F}_{\text{Non-MPC}} - \overline{F}_{\text{MPC}}}{\overline{F}_{\text{MPC}}} \times 100\%
\]

\[
\text{Index}_P = \frac{\overline{P}_{\text{Non-MPC}} - \overline{P}_{\text{MPC}}}{\overline{P}_{\text{MPC}}} \times 100\%
\]

On average, MPC-based method improved the performance index by 13.44% and 15.78%, respectively.

<table>
<thead>
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<th></th>
<th>Uncontrolled</th>
<th>Constrained</th>
<th>Difference</th>
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<tbody>
<tr>
<td>Non-MPC day-ahead</td>
<td>$26,645</td>
<td>$25,688</td>
<td>$957</td>
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<tr>
<td>MPC-based</td>
<td>$25,807</td>
<td>$24,985</td>
<td>$822</td>
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<tr>
<td>Perfect forecasting</td>
<td>$23,838</td>
<td>$23,724</td>
<td>$114</td>
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Total operational costs ($) under constrained PEV charging scheme over 30 trials

Distribution losses (kWh) under constrained PEV charging scheme over 30 trials