UNIVERSITY OF MICHIGAN-DEARBORN

Model Predictive Control-based Power Dispatch for Distribution Systems Considering Plug-in Electric Vehicle Charging Uncertainty

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

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Transportation sector consumes 1/3 of total energy in U.S.A.

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

Getting charged up about a gasoline-free future!

[1] **W. Su**, H. Rahimi-Eichi, W. Zeng, and M.-Y. Chow, "A Survey on the Electrification of Transportation in a Smart Grid Environment," *IEEE Trans. on Industrial Informatics*, vol.8, no.1, pp.1-10, Feb. 2012.
(2013 IEEE Industrial Electronics Society Student Best Paper Award)

1 Million	PHEVs/PEVs on the road by	2015
425000	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

Projected Plug-in Vehicle Market Share

Plug-in Electric Vehicles are coming !!!

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

250 million vehicles
X 10%
<u>X 10kW</u>
250 GW
1,000 GW (total U.S. installed generation capacity)

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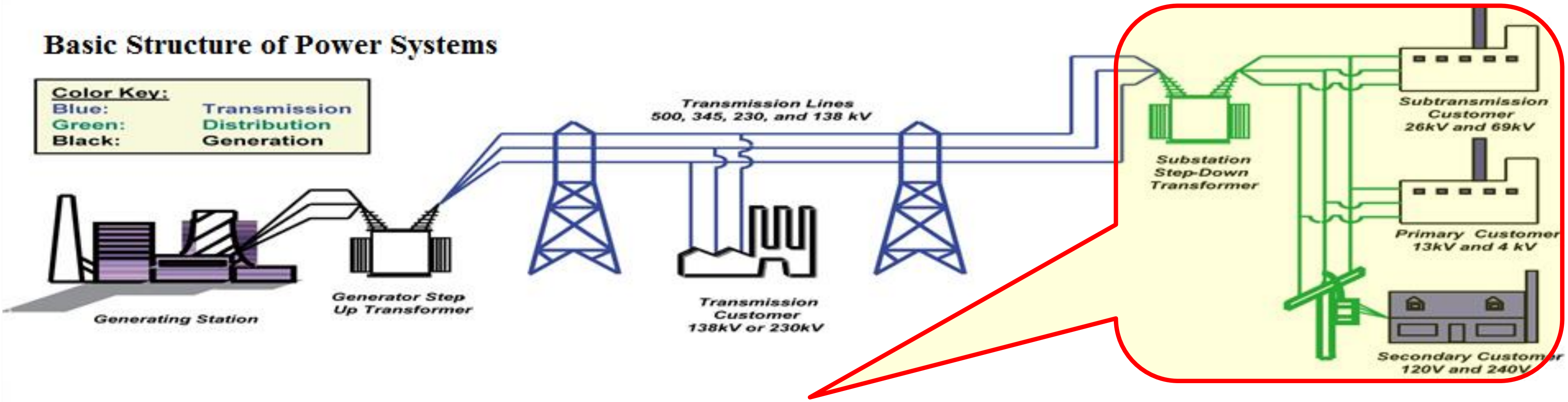

Study effects of the aggregate behavior of PEV charging loads on power grids

↓

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.

[1] **W. Su**, J. Wang, K. Zhang, and A.Q. Huang, "Model Predictive Control-based Power Dispatch for Distribution System Considering Plug-in Electric Vehicle Uncertainty", *Electric Power Systems Research*, vol.106, pp.29-35, Jan. 2014.

[2] **W. Su**, and J. Wang, "Energy Management Systems in Microgrid Operations," *The Electricity Journal*, vol.25, no.8, pp.45-60, Oct. 2012.

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.

$$Min \sum_{i=k}^{k+N-1} F(\hat{x}(i), \hat{u}(i)) \qquad \begin{array}{ll} \hat{x}(k) = x(k) & \\ \boxed{\hat{x}\,(i+1) = A\hat{x}(i) + B\hat{u}(i)} & i = k, k+1, \ldots, k+N-1 \\ g\big(\hat{x}(i), \hat{u}(i)\big) \leq 0 & i = k, k+1, \ldots, k+N-1 \end{array}$$

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

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 $x(k+1)$.

[1] E.F. Camacho, and C. Bordons, *Model Predictive Control,* 2nd ed. New York, USA: Springer, July 30, 2004.

[2] E. Gallestey, A. Stothert, M. Antoine and S. Morton, “Model predictive control and the optimization of power plant load while considering lifetime consumption,” *IEEE Trans. on Power Systems,* vol. 7, no.1, pp.86-191, Feb 2002.

- Look-ahead power dispatch
  - A multi-step optimization problem
  - Consider the inter-temporal constraints and benefits

One-step solution at the current time t

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

Subject to

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

$$P_{j,\min} \le P_j(t) \le P_{j,\max} \qquad P_{k,\min} \le P_k(t) \le P_{k,\max} \qquad SoC_{k,\min} \le SoC_k(t) \le SoC_{k,\max}$$

$$\Delta P_{j,\min} \le P_j(t) - P_j(t-1) \le \Delta P_{j,\max} \qquad \Delta P_{k,\min} \le P_k(t) - P_k(t-1) \le \Delta P_{\mathrm{k,max}}$$

Two-step solution at the current time t

$$\text{Min } [F(t) + F(t+1)]$$

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

Subject to

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

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

$$P_{j,\min} \le P_j(t) \le P_{j,\max} \qquad P_{k,\min} \le P_k(t) \le P_{k,\max} \qquad SoC_{k,\min} \le SoC_k(t) \le SoC_{k,\max}$$

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$$\Delta P_{j,\min} \le P_j(t) - P_j(t-1) \le \Delta P_{j,\max} \qquad \Delta P_{k,\min} \le P_k(t) - P_k(t-1) \le \Delta P_{\mathrm{k,max}}$$

$$\Delta P_{j,\min} \le P_j(t+1) - P_j(t) \le \Delta P_{j,\max} \qquad \Delta P_{k,\min} \le P_k(t+1) - P_k(t) \le \Delta P_{\mathrm{k,max}}$$

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

$$DEV^{H}_{MPC}(t) = DEV^{H-h}(t) + DEV^{h}(t). \quad h \le H,\ t = i+1, \ldots, i+N-1$$

$$DEV^{h} = f\ (h, SOC, Cap, T_{in}, T_{out}).$$

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4. Solve a deterministic optimization problem based on look-ahead finite-horizon prediction (next N hours)

Minimize $$F = \sum_t \sum_j c_j(P_j(t)) + \sum_t \sum_k c_k(P_k(t)) + \sum_t c_{grid}(P_{grid}(t)). \quad t = i, i+1, \ldots, i+N\text{-}1$$

$$U^* = \{u(i), u(i+1), \ldots, u(i+N-1)\} \qquad u(i) = \{P_j(i), P_k(i)\}.$$

5. Only perform the first step of the open-loop optimal control sequences $u(i)$

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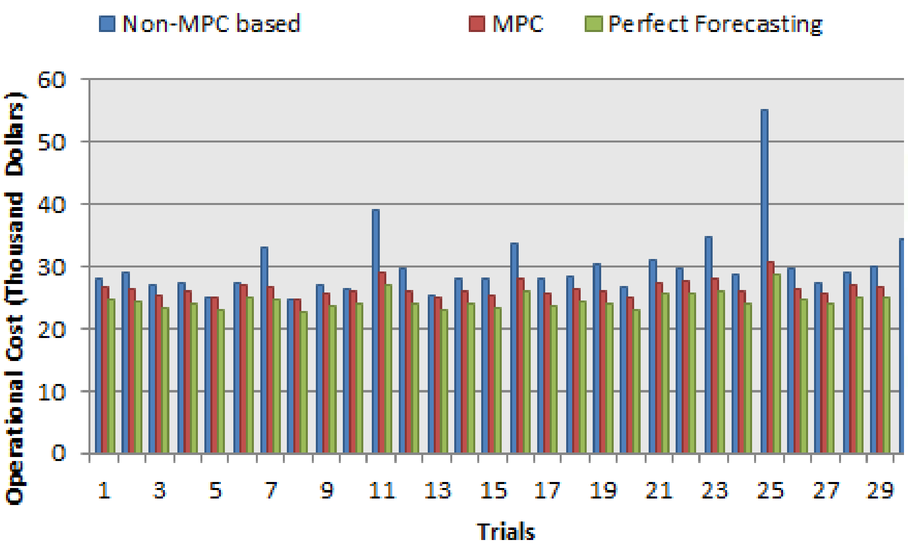
The MPC-based approach effectively compensates the PEV charging uncertainty by incorporating the most updated real-time information at each time step.

$$Index_F = \frac{\overline{F}_{Non-MPC} - \overline{F}_{MPC}}{\overline{F}_{MPC}} \%$$

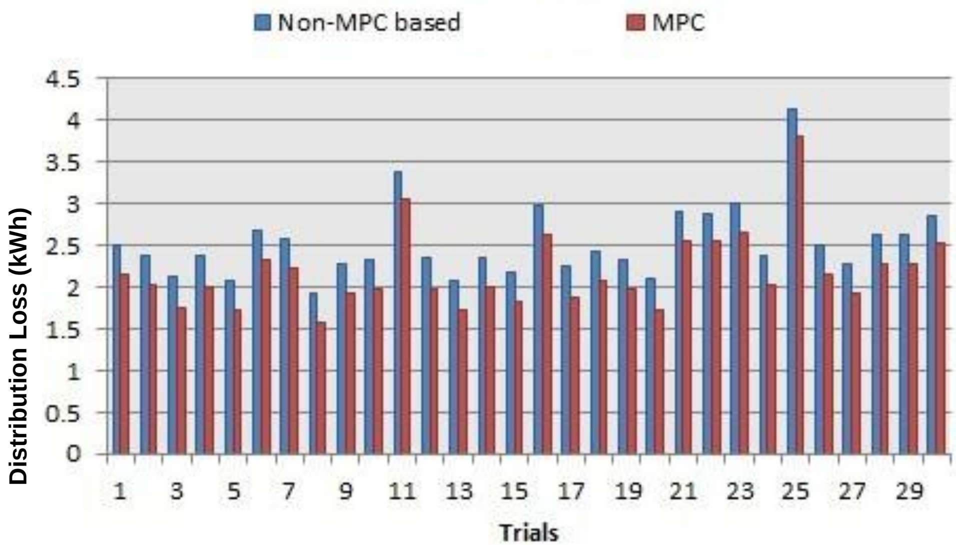
$$Index_P = \frac{\overline{P}_{Non-MPC} - \overline{P}_{MPC}}{\overline{P}_{MPC}} \%$$

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

	Uncontrolled	Constrained	Difference
Non-MPC day-ahead	F = \$26,645	F = \$25,688	\$957
MPC-based	F = \$25,807	F = \$24,985	\$822
Perfect forecasting	F = \$23,838	F = \$23,724	\$114



Total operational costs ($) under constrained PEV charging scheme over 30 trials



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

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