Unit Commitment for Sustainable Integration of Large-Scale Wind Power and Responsive Demand

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Acknowledgment
Electric Energy Systems Group (EESG)

http://www.eesg.ece.cmu.edu

• A multi-disciplinary group of researchers from across Carnegie Mellon with common interest in electric energy.

• Truly integrated education and research

• Interests range across technical, policy, sensing, communications, computing and much more; emphasis on systems aspects of the changing industry, model-based simulations and decision making/control for predictable performance.
Outline

• Wind power and demand side management—new sources of complexity
• Problem formulation for integrating wind and elastic demand—centralized UC/MPC; an example
• Scalability problem in centralized UC and UC market implementation—common challenge/approach
• Temporal vs spatial LR issue --basic efficiency/emissions concern with today’s UC
• Managing complexity—Distributed Interactive Unit Commitment (DIUC)
• Numerical example/comparison with benchmark solution- Integration of >50% wind
New source of complexity

- Supply the expected load with whatever produced by intermittent resources combined with other traditional power plants.

Today: Choose output levels from conventional power plants to meet the expected “net load” at minimum cost.
Unit commitment for sustainable integration of wind and demand side

- **Net system demand function** of system imbalance; greatly complicates the unit commitment problem
  - number of states potentially huge in inelastic demand case;
  - number of decision variables potentially huge in the demand elastic case.

- **Two qualitatively different methods**
  - **Centralized UC**—Demand, wind and generation cost functions short-run marginal cost; UC constraints explicit at the ISO level.
  - **Distributed Interactive UC (DIUC)**—When demand and cost functions account for UC constraints (DIUC) [1—6]; computationally manageable and provable lower bound performance under certain conditions.
Better Prediction of Intermittent Resources?

More efficient utilization of intermittent resources

More reliable operation of intermittent resources
Managing wind power—our approach [5]

• Actively control the output of available intermittent resources to follow the trend of time-varying loads.

• By doing so, the need for expensive fast-start fossil fuel units is reduced. Part of the load following is done via intermittent renewable generation.

• The technique used for implementing this approach is called model predictive control (MPC) [5].

• Implicit value of storage
Centralized MPC -- Benchmark

- Predictive model of load and intermittent resources are necessary.
- Optimization objective: minimize the total generation cost.
- Horizon: 24 hours, with each step of 5 minutes.
**Problem 3A:** Centralized MPC-based Dispatch with Inelastic Demand

Solve: \[
\min_{P_G} \sum_{k=1}^{K} \sum_{i \in G} \left( C_i(P_{G_i}(k)) \right), \quad i \in G \tag{39}
\]

Subject to: \[
\sum_{i} P_{G_i}(k) = \sum_{z} \hat{L}_z(k), \quad i \in G, \quad z \in Z; \tag{40}
\]

\[
\hat{L}_z(k) = f_z(L_z(k - 1)), \quad z \in Z; \tag{41}
\]

\[
\hat{P}_{G_j}^{\text{max}}(k) = g_j(\hat{P}_{G_j}^{\text{max}}(k - 1)); \tag{42}
\]

\[
\hat{P}_{G_j}^{\text{min}}(k) = h_j(\hat{P}_{G_j}^{\text{min}}(k - 1)); \tag{43}
\]

\[
\hat{P}_{G_j}^{\text{min}} \leq P_{G_j}(k) \leq \hat{P}_{G_j}^{\text{max}}, \quad j \in G_r; \tag{44}
\]

\[
P_{G_i}^{\text{min}} \leq P_{G_i}(k) \leq P_{G_i}^{\text{max}}, \quad i \in G \setminus G_r; \tag{45}
\]

\[
|P_{G_i}(k + 1) - P_{G_i}(k)| \leq R_i, \quad i \in G; \text{ and,} \tag{46}
\]

\[
|F(k)| \leq F^{\text{max}}. \tag{47}
\]
Problem 3B: Centralized MPC-Based Dispatch with Elastic Load

Solve: \( \min_{P_{G_i}, L} \sum_{k=1}^{K} \left( \sum_{i \in G} (C_i(P_{G_i}(k))) - \sum_{z \in Z} (B_z(L_z(k))) \right), \)  

s.t. \( \sum_{i \in G} P_{G_i}(k) = \sum_{z \in Z} L_z(k); \)  

\( \hat{P}_{G_r}^{\text{max}}(k) = g_j(\hat{P}_{G_r}^{\text{max}}(k-1)), r \in G_r; \)  

\( \hat{P}_{G_r}^{\text{min}}(k) = g_j(\hat{P}_{G_r}^{\text{min}}(k-1)), r \in G_r; \)  

\( \hat{P}_{G_j}^{\text{min}} \leq P_{G_j}(k) \leq \hat{P}_{G_j}^{\text{max}}, j \in G_r; \)  

\( P_{G_i}^{\text{min}} \leq P_{G_i}(k) \leq P_{G_i}^{\text{max}}, i \in G \setminus G_r; \)  

\( |P_{G_i}(k+1) - P_{G_i}(k)| \leq R_i, i \in G; \text{ and,} \)  

\( |F(k)| \leq F^{\text{max}}. \)
Model Predictive Control—Based

- MPC is receding-horizon optimization based control.
- At each step, a finite-horizon optimal control problem is solved but only one step is implemented.
- MPC has many successful real-world applications.
Numerical Example

Compare the outcome of ED from both the conventional and proposed approaches.
<table>
<thead>
<tr>
<th></th>
<th>Conventional cost over 1 year *</th>
<th>Proposed cost over the year</th>
<th>Difference</th>
<th>Relative Saving</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$ 129.74 Million</td>
<td>$ 119.62 Million</td>
<td>$ 10.12</td>
<td>7.8%</td>
</tr>
</tbody>
</table>

Rethinking the problem—
limits to complexity

• Clear that today’ MPC algorithms not scalable as of now;
• Typical approximation—LR w.r.t. time; assumes hierarchical time scale separation of SCED and UC
• LR w.r.t. to time questionable with persistent changes in system inputs; complexity will grow with new technologies (physics vs. binary decisions);
The basic efficiency/emissions concern

• Natural “optimal” schedules of different technologies very different; horizontal vs. vertical unit commitment

• Brute-forcing all technologies to re-commit using common clock is generally very inefficient

• Two possible solutions:
  - centralized multi-stage UC over several time horizons; still very complex
  - interactive UC between the resources and system operators; no LR wrt time; LR wrt units
• Decomposition over (portfolio) of resources critical; otherwise, the problem is not solvable; this is particularly true when combining with line switching
• Proposed new approach-Distributed Interactive UC (DIUC) [2-7]
  - LR w.r.t. (portfolio of) units NOT w.r.t. time
  - for the changing industry (distributed, interactive)
  - for the regulated industry (centralized algorithm)
Basic idea of minimally coordinated self-dispatch —Distributed Interactive UC (DIUC)

• Different technologies perform look-ahead decision making given their unique temporal and spatial characteristics and system signal (price or system net demand); they create bids and are cleared by the layers of coordinators

• Putting Auctions to Work in Future Energy Systems

• We illustrate next a supply-demand balancing process in an energy system with wind, solar, conventional generation, elastic demand, and PHEVs.
Our Proposed Framework: DIUC

Look-ahead Dispatch with Active Load Management
At Generator Level—Primal Problem

Solve: \[
\max_{P_{G_i}} \sum_{k=1}^{K} (\lambda_i(k) \times P_{G_i}(k) - C_i(P_{G_i}(k))), \quad k = 1, \ldots, K
\]

s.t. \(\lambda_i(k) = \lambda_i^{DA}(H)\), if interval \(k\) in the hour \(H\);

\[
\hat{P}_{G_j}^{\max}(k) = g_j(\hat{P}_{G_j}^{\max}(k - 1), \ldots, \hat{P}_{G_j}^{\max}(k - n_j));
\]

\[
\hat{P}_{G_j}^{\min}(k) = h_j(\hat{P}_{G_j}^{\min}(k - 1), \ldots, \hat{P}_{G_j}^{\min}(k - n_j));
\]

\[
\hat{P}_{G_j}^{\min} \leq P_{G_j}(k) \leq \hat{P}_{G_j}^{\max}, \quad i \in G;
\]

\[
|P_{G_i}(k + 1) - P_{G_i}(k)| \leq R_i, \quad i \in G.
\]

Max(Total Profit)

Predicted price

Available Generation Prediction

Gen Capacity Constraint

Ramp Rate Constraints

Note: In regulated industry – predicted net system demand
Main ideas of Adaptive Load Management (ALM)

• Reflecting various end-users’ needs and preferences into demand response
  – End-users’ info on preference sent to system
  – Mapping physical preference into economic preference → demand function

• (current systems) top-down control of loads → (future systems) two-way communicative and adaptive control

• Load aggregators’ role
  – Mediator between system/market and end-users
  – **Value of aggregating different resources and risk management**
    • Different load profiles, inelastic and elastic demands, distributed energy resources (DER), etc.
Today’s demand response scheme: 
Direct load control

- One-way flow of information
  - Load management conducted by utilities
  - Top-down control

- Exclusive contracts between supply and demand

- Direct load control
  - Regardless of end-users’ preferences
  - No access to market information for end-users
  - End-users’ information invisible to system
Adaptive Load Management (ALM) – Look-ahead distributed self-dispatch

- **Problem setup**
  - 10 end-users with different temperature preferences
  - Optimizing energy usage over 24 hours
    - Hourly-varying electricity price given (real-time pricing)
    - Outdoor weather temperature given

<table>
<thead>
<tr>
<th>End-user index</th>
<th>Temperature setpoints (°F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>68</td>
</tr>
<tr>
<td>2</td>
<td>70</td>
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<tr>
<td>3</td>
<td>72</td>
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<td>9</td>
<td>72</td>
</tr>
<tr>
<td>10</td>
<td>73</td>
</tr>
</tbody>
</table>

Hourly real-time pricing rates
Primal problem at the demand level

- Obtaining individual demand function subject to temperature comfort level

\[
\min_{\{x_i\}} \sum_{k=k_0}^{k_0+N} \left[ \lambda^L_A[k] \cdot x_i[k] + \left( T_i[k] - T_i^{\text{max}} \right)^2 + \left( T_i[k] - T_i^{\text{min}} \right)^2 \right]
\]

where \( T_i[k+1] = A_i T_i[k] + B_i x_i[k] \)

subject to \( T_i^{\text{min}} \leq T_i[k] \leq T_i^{\text{max}} \) for all \( k \)

- Obtain different \( x_i[k] \)s for different \( \lambda[k] \)s to infer demand functions

\( \rightarrow \) PHYSICS AT PLAY
Demand function

- **Objective**
  - To model price-responsive loads to integrate into the system optimization
  - To include information of end-users’ utility (benefit) in system optimization
  - To see if price-responsive loads compensate with volatile intermittent resources

- **What it is**
  - Function of end-users’ willingness-to-pay with respect to electricity demand quantity
  
  \[ d(P_D) = aP_D + b \]
Demand function (cont’d)

• How to obtain
  – Calculate optimal energy usage by hours with a given electricity price
  – Perturb the given price by a certain percentage (e.g. ±20%) and re-calculate optimal energy usage with new prices
  – Curve-fit price-demand quantity pairs to identify the parameters of a demand function
Resulting bid curves by demand—Result of solving primal problem

- Demand functions of end-user #1
Information flow of ALM—Auctions Put to Work (Primal-Dual Solution Interactions)

- **Tertiary level**: Load aggregator III
- **Secondary level**: Load aggregator II
- **Primary level**: Load aggregator I

**Market**
- **Bid function**: $b(\lambda)$
- **Demand function**: $b(\lambda^I)$
- **Market price**: $\lambda$
- **End-user price**: $\lambda^I$

- **End-user**
- **Load aggregator**s
Information flow of ALM

• Primary layer (from end-users to load aggregators)
  – Physical preference $\rightarrow$ economic preference
  – Individual demand function

• Secondary layer (from load aggregators to market)
  – Aggregating end-users’ energy usage + risk management
  – Optimal energy purchase/market transaction given system price

• Back to primary layer (from load aggregators to end-users)
  – Energy price adjusted according to system/locational price: $\lambda^{\text{LA}}$
    as a function of $\lambda^{\text{system}}$
Bid curves for different technologies—result of distributed MPC

- Price-responsive demand function $b_{\text{elas}}(t)$
- Inelastic demand $b_{\text{inelas}}(t)$
- Gen Supply Function $b_{\text{gen}}(t)$
- PHEV (supply mode) $b_{\text{PHEV}}(t)$

Price (\$/MWh) vs. Power (MW) graph with points $P_{\text{gmin}}(t)$, $P_{\text{gmax}}(t)$.
Implementation in Markets—DIUC---Primal-Dual Solution Interactions (spatial/not temporal)

The System Operator: Maximize Social Welfare While Observing Transmission Constraints

Supply function

\[ S_i(P_i(k+1), \lambda_i(k+1)) \]

Clearing Price

\[ \lambda_i(k) \]

Demand function

\[ B_j(P_{Lj}(k+1), \lambda_j(k+1)) \]

Clearing Price

\[ \lambda_j(k) \]

Predictive Model [ and MPC Optimizer

\[ \hat{P}_i^{\text{max}}(k+1) \]

\[ \hat{P}_i^{\text{min}}(k+1) \]

\[ \lambda_i(k+1) \]

Generator i

Aggregated Predictive model [ and MPC Optimizer

\[ x_j^{\text{max}}(k+1) \]

\[ x_j^{\text{min}}(k+1) \]

\[ \hat{\lambda}_j(k+1) \]

Load j


Integrating fossil, wind, solar and demand side and PHEVs

Compare the outcome of ED from both the centralized and distributed MPC approaches.
BOTH EFFICIENCY AND RELIABILITY MET
Preliminary Results: 50% Wind

MPC-based DYMONDS Dispatch with 50% Wind

Preliminary Results: 50% Wind

Potential Savings

Cost Difference between MPC-based Dispatch for 50% Wind Case

Dollars

Time Steps (10 minutes interval)

Optimal Control of Plug-in-Electric Vehicles: Fast vs. Smart

- **Fast Charging**
  - Residential Load
  - PHEV Load at 10% Fleet Penetration

- **Goal of Smart Charging**
  - Residential Load
  - PHEV Load at 10% Fleet Penetration

Graphs showing the percent of peak load over the hours of the day for both fast and smart charging scenarios.
Information flow—Fantastic Use of Multi-layered Dynamic Programming
Plug-and-Play (No Coordination)?

Total generation and total demand imbalances in 50% wind case
Smart Grid [1]
Distributed Interactive UC--DIUC

• Allow different technologies to optimize in anticipation of system conditions while taking into account their unique inter-temporal constraints and sub-objectives;

• The distributed optimization done in a look-ahead dynamic way at the resource level to create cost functions (bidding functions for both supply and demand)

• Result: Lower electricity prices and higher efficiency; minimized overall UC cost
Our general framework

• Use adequate performance measures
• Perform meaningful spatial decomposition and aggregation (zoned, portfolios)
• Iterate to ensure that the inter-dependencies are accounted for by inter-actively exchanging information
  - Even coordinated software must account for the information that is iteratively updated from the non-utility resources
  - In the market environment it becomes necessary to reconcile choice and system-wide objectives
• Use predictions create bid functions (instead of numbers) to control software performance
References

• Ilic, Marija “Dynamic Monitoring and Decision Systems (DYMONDS) and Smart Grids: One and the Same, CMU EESG WP 019, October 2009.
• [2] Ilic, Marija “IT-enabled Rules, Right and Responsibilities (3Rs) for Efficient Integration of Wind and Demand Side Response”, Public Utility Fortnightly Magazine, Dec 2009.