Optimal Tradeoffs between Demand Response and Storage with Variable Renewables

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Outline

Motivation

- In the analysis and optimization of traditional power system, one key binding constraint is

$$\text{supply}(t) = \text{demand}(t) \quad \forall t$$

- Recently, fueled by the advances in technologies, we can potentially relax this constraint by (1) demand response (DR) and (2) energy storage
  - Both techniques effectively shift the supply/demand in the time horizon
  - Deploying such techniques can potentially improve the "social utility" of a power system (e.g. Su et al. 2011)
- What are the tradeoffs between them?

Tradeoffs between DR and Storage

- Operational Tradeoffs
  - Assume both automated DR and storage are available
  - Sometimes it is desirable to shift supply/demand in the time horizon to improve the power system "social utility"
  - Under what circumstances it is more desirable to use DR in stead of storage, and vice versa?
- Tradeoffs in Facility Planning
  - Which technique is more cost-effective?
  - Suppose automated DR is already implemented, is it worthy to add a battery to the power system?

Objective

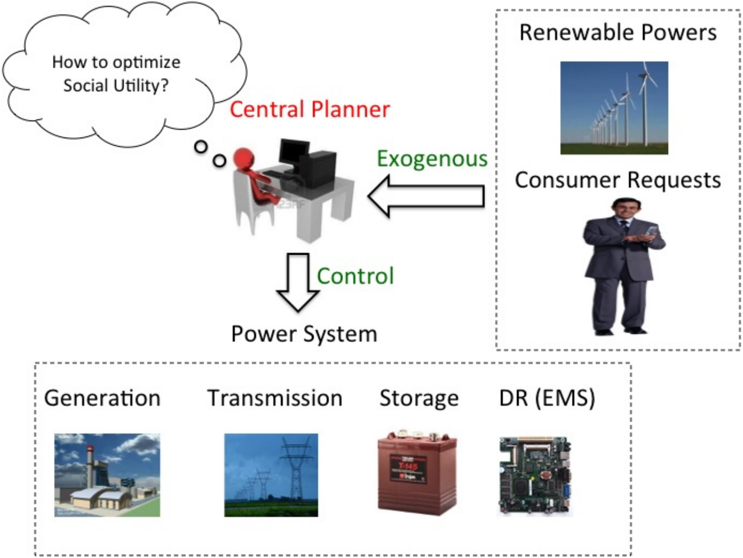
- Another key component of smart grid is the renewable generation
  - E.g. energy derived from wind, sun and tides
  - Significant challenges in power system operations due to their stochastic nature
- In this project, we consider power systems incorporating renewable generation, demand response and energy storage
- Our goal is to characterize the tradeoffs between demand response and energy storage in such power systems

Outline

"Central Planner" Assumption

- In practice, different components of a smart grid are owned and operated by different agents
  - The interaction between these agents forms the electricity market
  - The "social utility" of a power system should be analyzed at an equilibrium under some electricity market mechanism
- In this project, we assume that the whole power system is controlled by a "central planner"
- This is motivated by the second theorem of welfare economics
  - Once an optimal scheduling strategy of the central planner is available, under suitable technical conditions, a competitive equilibrium (CE) achieving the optimal social utility can be derived

“Central Planner” Assumption



Motivation for Power System Partition

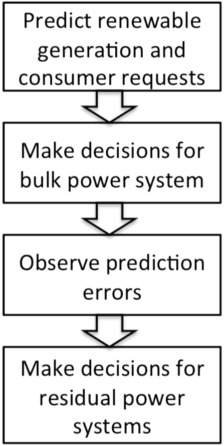
- Observation 1: although available renewable powers and consumer requests cannot be completely predicted beforehand, however, the relative prediction errors tend to be small
- Observation 2: different components of a power system have different time constants
    - the central planner could delay the operations on "fast devices" until the prediction errors are realized
- As has been discussed in Su et al. 2011, these observations motivate us to partition the power system into one bulk power system and (possibly multiple) residual power systems

Bulk Power System vs. Residual Power System

	Bulk Power System	Residual Power System
Generators	base-load/intermediate	fast-ramping
	predicted component of renewable generators	unpredicted component renewable generators
Storage	bulk	fast-response
Consumer Request	predicted component	unpredicted component
Power Flow	AC/DC	DC
Number of Buses	multiple buses	single bus
System Dynamics	time-varying deterministic	time-invariant stochastic
Optimization Techniques	OPF	stochastic control
Decision Time	before observing the prediction errors	after observing the prediction errors

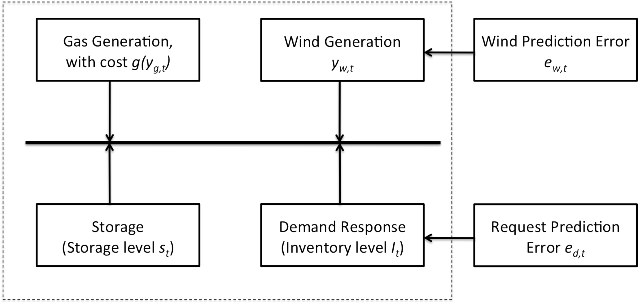
Timeline at Each Time Period

1. The central planner predicts the current and future consumer requests and renewable powers
2. He solves the receding-horizon OPF for the bulk power system, and implements the first step of the obtained strategy
3. He observes the realization of the prediction errors
4. He derives the optimal control for the residual power systems based on dynamic programming



Single-Bus Residual Power System

- Many literatures have been dedicated to
  - The prediction of consumer requests or renewable powers
  - Solving OPF of large-scale power systems
- We focus on optimizing the social utility in a residual power system and analyzing the optimal tradeoffs between DR and storage



Outline

Stochastic Control Formulation

- Formulate the social utility optimization in a residual power system as an infinite-horizon discounted stochastic control problem
  - **State** $x_t \in \Re^4$: (1) "inventory level" of the backlogged requests, (2) battery charging level, and (3) observed prediction errors
  - **Action** $a_t \in \Re^2$: (1) gas plant generation and (2) battery charging rate
  - **Dynamics**: balance equations of (1) backlogged requests and (2) battery charging level
  - **Exogenous** prediction errors are assumed to be i.i.d.
  - **Constraints:** (1) Battery capacity limit and charging/discharging rate limit and (2) Bulk system compensation requirement
  - **Instantaneous "social cost"**: (gas plant generation cost) + (dis-utility of the "representative consumer" on backlogged requests)

Dynamic Programming Solution

- Theoretically, this stochastic control problem can be solved based on dynamic programming
- However, in practice, it is challenging to derive closed-form solutions
- Note the dimension of the dynamic system is low ($x \in \Re^4$ and $a \in \Re^2$), thus we can numerically solve this DP problem
  - Discretize the state/action space
  - Numerically compute the cost-to-go function based on value iteration (or other methods)
  - Derive a (near) optimal control based on this cost-to-go function

Preliminary Analysis Result

Assumption 1

Assume that both the *gas plant generation cost function* and the *dis-utility function* are strictly increasing and strictly convex

Theorem 1

Under Assumption 1, if we ignore the costs of batteries and EMS, then from the perspective of the central planner

- EMS is desirable
- A battery with larger capacity limit or higher rate limit is desirable

Facility Planning

- In practice, implementing batteries and EMS is costly
- For any facility plan, we can compute its "value" by (numerically) solving the associated stochastic control problem
  - "value" is the minus of the cost-to-go at a specified initial condition
- For each facility plan,

$$\text{expected profit} = (\text{expected value increase}) - \ (\text{incurred cost})$$

- The optimal facility plan is the one that results in the highest expected profit

Outline

Ongoing and Future Work

- Currently we are working on a numerical case study
  - We have just obtained data from GE
  - Try to find the optimal battery capacity and rate limit for a residual power system (with and without EMS)
  - "optimal" = highest expected profit
- Future work:
  - Implement the complete scheduling strategy of the central planner (i.e. for both the bulk power system and residual power systems) in a practical case
  - Derive the *optimal electricity pricing* based on the optimal scheduling strategy (i.e. characterize a CE achieving the optimal social utility)