

Capacity Expansion of Stochastic Power Generation under Two-Stage Electricity Markets

SMATAD 2017 (Fuengirola, Spain)

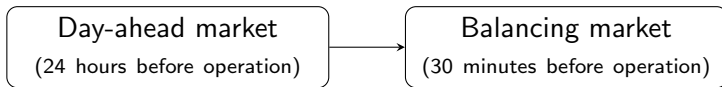
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May, 20, 2017

Motivation

- Stochastic power generation (wind, solar) depends on weather
- Stochastic power generation is hard to forecast (even 24h in advance)
- Energy markets usually have two trading floors



- Stochastic units have imbalance costs due to forecast errors
- Capacity expansion problems aim at determining the optimal type, quantity and location of power plants to be constructed
- Capacity expansion has to account for the following features of stochastic power generation:
 - Time variability ✓
 - Long-term uncertainty ✓
 - Short-term uncertainty ✗

Contribution

- To develop generation expansion models that explicitly account for short-term **forecast errors** of stochastic power production.
- To analyze the effect of **market design** on generation expansion by considering two paradigmatic market-clearing mechanisms.
- To investigate the impact of **competition** at the investment level in the generation expansion of stochastic power units.

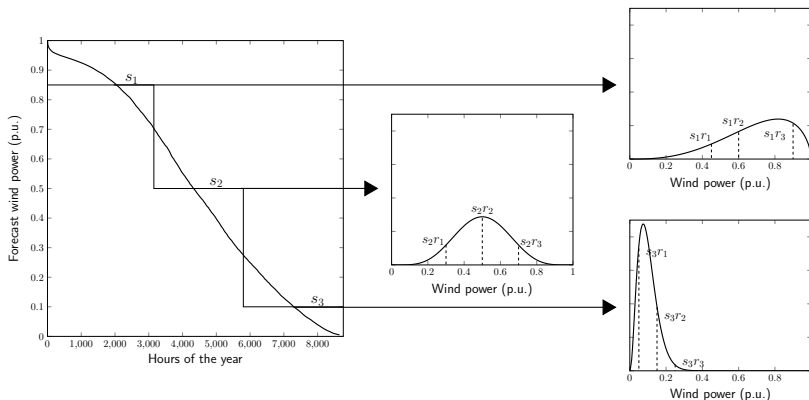
Modeling overview

- Static approach with a single representative year
- Energy-only market
- Duration curves to capture time variability
- Long-term uncertainty not included
- Unit commitment constraints disregarded
- Characterization of short-term forecast errors

Characterization of short-term forecast errors

Day-ahead market
(24 hours before operation)

Balancing market
(30 minutes before operation)



Modeling overview

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- Competition at the investment stage (central planner and collusion)

Competition at investment

Central planner

Investment + operation
minimize total cost

- Perfect competition
- Easier to model
- Benchmark

Collusion

Investment: maximize profit

$\downarrow \bar{p}^W$

Operation: minimize cost

- Imperfect competition
- Strategic investment
- Sequential game

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- Market design (day-ahead, efficient and inefficient)

Market design

Day-ahead market

Day-ahead

- No balancing market
- No forecast errors
- Fully flexible
- Commonly used approach

Efficient market

Day-ahead
+
balancing

- Expensive day-ahead
- Cheaper balancing
- Low total cost
- Simultaneous reserve and energy

Inefficient market

Day-ahead

Φ^D

Balancing

- Cheap day-ahead
- Expensive balancing
- High total cost
- Reserves after energy

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- Characterization of short-term forecast errors
- Competition at the investment stage (central planner and collusion)
- Market design (day-ahead, efficient and inefficient)
- Six generation expansion models to be compared

Central planner

Collusion

DayMC

EffMC

IneMC

DayMC

EffMC

IneMC

Central, perfect forecast, day-ahead market

$\begin{aligned} \text{Min}_{\bar{p}^W, \Phi_s^D} \quad & \mathcal{C}^I(\bar{p}^W) + \sum_s \tau_s \mathcal{C}^D(\Phi_s^D) \\ \text{s.t.} \quad & f(\bar{p}^W) \leq 0 \\ & g(\bar{p}^W, \Phi_s^D; \rho_s) \leq 0, \quad \forall s. \end{aligned}$	<table> <tr> <td>s</td><td>System state index</td></tr> <tr> <td>τ_s</td><td>System state weight</td></tr> <tr> <td>ρ_s</td><td>System state parameters</td></tr> <tr> <td>\bar{p}^W</td><td>Investment decisions</td></tr> <tr> <td>$\mathcal{C}^I(\cdot)$</td><td>Investment cost</td></tr> <tr> <td>$f(\cdot)$</td><td>Investment constraints</td></tr> <tr> <td>Φ_s^D</td><td>Dispatch decisions</td></tr> <tr> <td>$\mathcal{C}^D(\cdot)$</td><td>Dispatch cost</td></tr> <tr> <td>$g(\cdot)$</td><td>Dispatch constraints</td></tr> </table>	s	System state index	τ_s	System state weight	ρ_s	System state parameters	\bar{p}^W	Investment decisions	$\mathcal{C}^I(\cdot)$	Investment cost	$f(\cdot)$	Investment constraints	Φ_s^D	Dispatch decisions	$\mathcal{C}^D(\cdot)$	Dispatch cost	$g(\cdot)$	Dispatch constraints
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For discrete investment decisions and linear functions \implies MIP

Central, imperfect forecast, efficient two-stage market

$$\begin{aligned}
 & \underset{\bar{p}^W, \Phi_s^D, \Phi_{sr}^B}{\text{Min}} && c^I(\bar{p}^W) + \sum_s \tau_s \left(c^D(\Phi_s^D) + \sum_r \pi_{sr} c^B(\Phi_{sr}^B) \right) \\
 & \text{s.t.} && f(\bar{p}^W) \leq 0 \\
 & && g(\bar{p}^W, \Phi_s^D; \rho_s) \leq 0, \quad \forall s \\
 & && h(\bar{p}^W, \Phi_s^D, \Phi_{sr}^B; \rho_s, \Delta\rho_{sr}) \leq 0, \quad \forall s, \forall r.
 \end{aligned}$$

r	Balancing scenario index	Φ_{sr}^B	Redispatch decisions
π_{sr}	Balancing scenario probability	$c^B(\cdot)$	Redispatch cost
$\Delta\rho_{sr}$	Parameter variations	$h(\cdot)$	Redispatch constraints

For discrete investment decisions and linear functions \implies MIP

Central, imperfect forecast, inefficient two-stage market

$$\begin{aligned}
 & \underset{\bar{p}^W, \Phi_s^D, \Phi_{sr}^B}{\text{Min}} && \mathcal{C}^I(\bar{p}^W) + \sum_s \tau_s \left(\mathcal{C}^D(\Phi_s^D) + \sum_r \pi_{sr} \mathcal{C}^B(\Phi_{sr}^B) \right) \\
 & \text{s.t.} && f(\bar{p}^W) \leq 0 \\
 & && h(\bar{p}^W, \Phi_s^D, \Phi_{sr}^B; \rho_s, \Delta\rho_{sr}) \leq 0, \quad \forall s, \forall r \\
 & && \Phi_s^D \in \arg \left\{ \begin{array}{l} \underset{\Phi_s^D}{\text{Min}} \quad \mathcal{C}^D(\Phi_s^D) \\ \text{s.t.} \quad g(\bar{p}^W, \Phi_s^D; \rho_s) \leq 0. \end{array} \right\} \forall s.
 \end{aligned}$$

- Particular use of bilevel programming to impose day-ahead merit order
- Discrete investment decisions and linear functions
- Replace the lower-level problem by its primal-dual formulation
- Linearize the products of continuous and binary variables
- We obtain a single-level mixed-integer linear programming problem

Collusion, perfect forecast, day-ahead market

$$\text{Max}_{\bar{p}^W, \Phi_s^D} \sum_s \tau_s \Pi^D (\Phi_s^D, \lambda_s^D) - \mathcal{C}^I (\bar{p}^W)$$

$$\text{s.t. } f(\bar{p}^W) \leq 0$$

Π^D Day-ahead profit
 λ_s^D Day-ahead price

$$(\Phi_s^D, \lambda_s^D) \in \arg \left\{ \begin{array}{ll} \text{Min}_{\Phi_s^D} & \mathcal{C}^D (\Phi_s^D) \\ \text{s.t.} & g(\bar{p}^W, \Phi_s^D; \rho_s) \leq 0 \end{array} \right\} \forall s$$

- Discrete investment decisions and linear functions
- Replace the lower-level problem by its primal-dual formulation
- Linearize profit expression using KKT conditions
- Linearize the products of continuous and binary variables
- We obtain a single-level mixed-integer linear programming problem

Collusion, imperfect forecast, efficient two-stage market

$$\begin{aligned}
 & \max_{\bar{p}^W, \Phi_s^D, \Phi_{sr}^B} \sum_s \tau_s \left(\Pi^D(\Phi_s^D, \lambda_s^D) + \sum_r \pi_{sr} \Pi^B(\Phi_{sr}^B, \lambda_{sr}^B) \right) - \mathcal{C}^I(\bar{p}^W) \\
 & \text{s.t. } f(\bar{p}^W) \leq 0 \\
 & \left(\begin{array}{cc} \Phi_s^D & \Phi_{sr}^B \\ \lambda_s^D & \lambda_{sr}^B \end{array} \right) \in \arg \left\{ \begin{array}{ll} \min_{\Phi_s^D, \Phi_{sr}^B} & \mathcal{C}^D(\Phi_s^D) + \sum_r \pi_{sr} \mathcal{C}^B(\Phi_{sr}^B) \\ \text{s.t.} & g(\bar{p}^W, \Phi_s^D; \rho_s) \leq 0 \\ & h(\bar{p}^W, \Phi_s^D, \Phi_{sr}^B; \rho_s, \Delta \rho_{sr}) \leq 0, \quad \forall r \end{array} \right\} \quad \forall s
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- Discrete investment decisions and linear functions
- Replace the lower-level problem by its primal-dual formulation
- Linearize profit expression using KKT conditions
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Collusion, imperfect forecast, inefficient two-stage market

$$\begin{aligned}
 & \text{Max}_{\bar{p}^W, \Phi_s^D, \Phi_{sr}^B} \quad \sum_s \tau_s \left(\Pi^D (\Phi_s^D, \lambda_s^D) + \sum_r \pi_{sr} \Pi^B (\Phi_{sr}^B, \lambda_{sr}^B) \right) - \mathcal{C}^I (\bar{p}^W) \\
 & \text{s.t.} \quad f(\bar{p}^W) \leq 0 \\
 & \left(\begin{matrix} \Phi_s^D & \Phi_{sr}^B \\ \lambda_s^D & \lambda_{sr}^B \end{matrix} \right) \in \arg \left\{ \begin{array}{l} \text{Min}_{\Phi_s^D, \Phi_{sr}^B, \lambda_s^D} \quad \mathcal{C}^D (\Phi_s^D) + \sum_r \pi_{sr} \mathcal{C}^B (\Phi_{sr}^B) \\ \text{s.t.} \quad h(\bar{p}^W, \Phi_s^D, \Phi_{sr}^B; \rho_s, \Delta \rho_{sr}) \leq 0 \\ \left(\Phi_s^D, \lambda_s^D \right) \in \arg \left\{ \begin{array}{l} \text{Min}_{\Phi_s^D} \quad \mathcal{C}^D (\Phi_s^D) \\ \text{s.t.} \quad g(\bar{p}^W, \Phi_s^D; \rho_s) \leq 0 \end{array} \right\} \end{array} \right\} \quad \forall s
 \end{aligned}$$

- Three-level optimization problem with particular structure since second-level variables (Φ_{sr}^B) do not enter the third-level problem.

Collusion, imperfect forecast, inefficient two-stage market

- Discrete investment decisions and linear functions
- Replace the third-level problem by its primal-dual formulation.
- For fix upper-level decisions, the resulting lower-level problem still satisfies the linearity constraint qualification.
- Replace the lower-level problem by its primal-dual formulation.
- Linearize the products of continuous and binary variables.
- The profit expression cannot be linearized.
- We obtain a single-level mixed-integer non-linear programming problem.
- We use an heuristic procedure to find a solution close to the optimal one and provide it as an initial point to the non-linear solver.

Danish case study

- 2 bus system (DK1, DK2) with 600MW transmission line
- Hourly demand and wind capacity factor of 2012
- Approximated supply cost function using aggregated conventional production and prices of 2012
- 25 system states (demand and wind variability)
- 10 balancing scenarios for each state (short-term wind uncertainty)
- Wind investment blocks of 50 MW
- No existing wind generating capacity

Danish case study

Table: Central-planner

	\bar{p}_{DK1}	\bar{p}_{DK2}	\bar{c}	ψ
DayMC	3500	2500	6834	42.9
EffMC	3500	2250	6999	40.2
IneMC	3450	2350	7067	39.4

Table: Collusion

	\bar{p}_{DK1}	\bar{p}_{DK2}	$\bar{\Pi}$	ψ
DayMC	2150	1950	612	29.4
EffMC	1300	1600	475	20.6
IneMC	300	2550	277	19.3

- Forecast errors reduce investments, cost, profit and renewable share
- An efficient market clearing reduces the impact of forecast errors
- Impact of forecast errors is larger for imperfect competition
- Forecast errors and market design also affects investment locations

Conclusions

- We have presented a family of generation expansion models for stochastic generating plants that account for the impact of short-term forecast errors. The models differ in the market design and competitiveness at the investment level.
- We have formulated some of these models as multi-level optimization problems and shown how to recast them, under certain assumptions, as single-level linear and non-linear optimization problems that can be solved using commercial software.
- We have provided the results of a case study based on the danish power system to show that forecast errors affect the install capacity of stochastic power plants and that an efficient short-term market can lead to higher investment in renewable power generation.

All details in...

Computers & Operations Research 70 (2016) 101–114



Contents lists available at [ScienceDirect](#)

Computers & Operations Research

journal homepage: www.elsevier.com/locate/caor



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Thanks for the attention!

Questions???

Website: <https://sites.google.com/site/slv2pm/>