## Impact of Forecast Errors on Expansion Planning of Power Systems with a Renewables Target DTU Summer School 2016

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## Long-term planning problem

- We want to determine the optimal capacity of generating units and transmission lines to
  - · satisfy future electricity demand
  - ensure a given share of renewable generation

at the minimum cost.

- Generation and transmission expansion planning models can be classified into
  - single-year (static) or multi-year (dynamic) models
  - deterministic or stochastic models



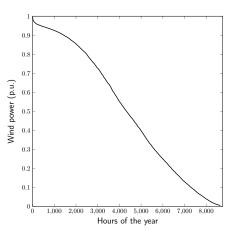
## Singe-year deterministic G-TEP

$$\underset{\overline{p}, \Phi_s^D}{\text{Min}} \quad \sum_s \tau_s \mathcal{C}^D \left( \Phi_s^D \right) + \mathcal{C}^I \left( \overline{p} \right) 
\text{s.t.} \quad \psi \geqslant \psi_{\text{target}} 
\quad f \left( \overline{p} \right) \leqslant 0 
\quad h^D \left( \Phi_s^D; l_s \right) = 0, \quad \forall s 
\quad g^D \left( \overline{p}, \Phi_s^D; \rho_s \right) \leqslant 0, \quad \forall s.$$

**G-T** capacities  $\Phi^D_s$ Operation decisions Index of system states sWeight of each state  $\tau_s$  $\mathcal{C}^D$ Operating cost  $\mathcal{C}^{I}$ Investment cost  $\psi$ Demand covered by renewables Electricity demand Capacity factor of renewables  $\rho_s$ Expansion constraints  $h^D$ Balance equation  $g^D$ Operating constraints

## Time variability in G-TEP

- Use of duration curves to characterize the variability throughout the planning horizon
- Duration curves are approximated using blocks



- G-T planning is made several years ahead and therefore, they face long-term uncertainty in:
  - Electricity demand growth
  - Fuel costs
  - Renewable electricity generation
- This uncertainty is usually modeled using scenarios (w) with different probabilities  $(\pi_w)$ .
- Planing decisions are then determined by solving a stochastic G-TEP





# EES-UE Bleecht: Ense

$$\begin{array}{ll}
\operatorname{Min}_{\overline{p},\Phi_{sw}^{D}} & \sum_{sw} \tau_{s} \pi_{w} \mathcal{C}^{D} \left( \Phi_{sw}^{D} \right) + \mathcal{C}^{I} \left( \overline{p} \right) \\
\text{s.t.} & \psi_{w} \geqslant \psi_{\text{target}}, \quad \forall w \\
f \left( \overline{p} \right) \leqslant 0 \\
h^{D} \left( \Phi_{sw}^{D}; l_{sw} \right) = 0, \quad \forall s, w \\
q^{D} \left( \overline{p}, \Phi_{sw}^{D}; \rho_{sw} \right) \leqslant 0, \quad \forall s, w.
\end{array}$$

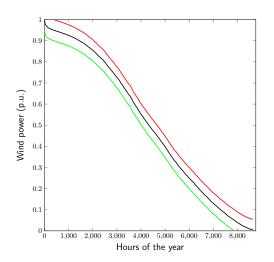
w Scenario index

 $\pi_w$  Scenario probability

 $l_{sw}$  Uncertain electricity demand

 $ho_{sw}$  Uncertain renewable capacity factor

## Long-term uncertainty in G-TEP

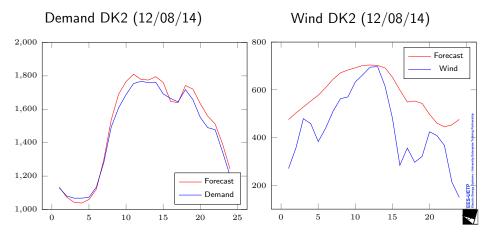




- The previous stochastic G-TEP takes into account the variability of demand and renewable production throughout the planning horizon and the long-term uncertainty of demand and renewable production
- However, the stochastic G-TEP disregards the short-term uncertainty of electricity demand and renewable capacity factor. That is, it is assumed that day-ahead dispatch decisions are made perfectly knowing the realization of these two parameters.

#### Short-term uncertainty

- Wind power production varies through time
- Wind power production is hard to predict in advance



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- How can we account for forecast errors within current generation and transmission capacity expansion models?
- What is the impact of these forecast errors on generation and transmission capacity expansion planning?
- What is the impact of the market design on generation and transmission capacity expansion planning?



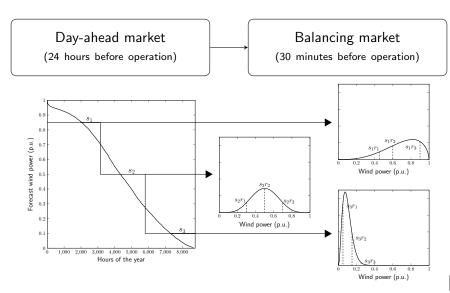


#### Some assumptions

- Single-year model (multi-year model in the paper)
- Focus on short-term system operation (no long-term uncertainty)
- Unit commitment costs are internalized through balancing offers
- No inter-temporal constraints (stationary process)
- Energy-only market with marginal pricing (no capacity payments)
- Perfect competitive market (central planner approach)
- Inelastic demand (high cost for load shedding)
- DC representation of the network



#### Two markets floors



#### Coordination between the two market floors

#### Inefficient market

Day-ahead: min  $\mathcal{C}^D(\Phi^D)$ 



Balancing: min  $C^B(\Phi^D, \Phi^B)$ 

#### Efficient market

Day-ahead + balancing

$$\min \, \mathcal{C}^D(\Phi^D) + \sum_r \pi_r \mathcal{C}^B(\Phi^D,\Phi^B)$$

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

- More expensive day-ahead
- Cheaper balancing
- Minimum total cost
- Simultaneous reserve and energy



- G-T expansion problem without forecast errors
- G-T expansion problem with forecast errors under efficient market
- G-T expansion problem with forecast errors under inefficient market





#### G-TEP without forecast errors

$$\underset{\overline{p}, \Phi_s^D}{\text{Min}} \quad \sum_{s} \tau_s \mathcal{C}^D \left( \Phi_s^D \right) + \mathcal{C}^I \left( \overline{p} \right) 
\text{s.t.} \quad \psi \geqslant \psi_{\text{target}} 
\quad f \left( \overline{p} \right) \leqslant 0 
\quad h^D \left( \Phi_s^D; l_s \right) = 0, \quad \forall s 
\quad g^D \left( \overline{p}, \Phi_s^D; \rho_s \right) \leqslant 0, \quad \forall s.$$

The electricity market modeled here can be interpreted as:

- A real-time market with completely flexible generating units able to instantaneously adapt their output to the status of the system
- A day-ahead market cleared with perfect forecasts of demand and renewable generation



#### G-TEP with forecast errors under efficient market

$$\underset{\overline{p}, \Phi_{s}^{D}, \Phi_{sr}^{B}}{\text{Min}} \quad \sum_{s} \tau_{s} \left( \mathcal{C}^{D} \left( \Phi_{s}^{D} \right) + \sum_{r} \pi_{sr} \mathcal{C}^{B} \left( \Phi_{sr}^{B} \right) \right) + \mathcal{C}^{I} \left( \overline{p} \right) \\
\text{s.t.} \quad \psi \geqslant \psi_{\text{target}} \\
f \left( \overline{p} \right) \leqslant 0 \\
h^{D} \left( \Phi_{s}^{D}; l_{s} \right) = 0, \quad \forall s \\
g^{D} \left( \overline{p}, \Phi_{s}^{D}; \rho_{s} \right) \leqslant 0, \quad \forall s \\
h^{B} \left( \Phi_{sr}^{B} \right) = 0, \quad \forall s, \forall r \\
g^{B} \left( \overline{p}, \Phi_{s}^{D}, \Phi_{sr}^{B}; \rho_{s}, \Delta \rho_{sr} \right) \leqslant 0, \quad \forall s, \forall r.$$

Balancing scenario index

 $\pi_{sr}$ 

Balancing scenario probability

 $\Phi_{aa}^{B}$  re-dispatch decisions

 $\mathcal{C}^B$ Balancing costs

variation of capacity factor  $h^B, q^B$  Balancing constraints

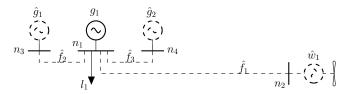
#### G-TEP with forecast errors under inefficient market

$$\begin{split} & \underset{\overline{p}, \Phi_{s}^{D}, \Phi_{sr}^{B}}{\text{Min}} & \sum_{s} \tau_{s} \left( \mathcal{C}^{D} \left( \Phi_{s}^{D} \right) + \sum_{r} \pi_{sr} \mathcal{C}^{B} \left( \Phi_{sr}^{B} \right) \right) + \mathcal{C}^{I} \left( \overline{p} \right) \\ & \text{s.t.} & \psi \geqslant \psi_{\text{target}} \\ & f \left( \overline{p} \right) \leqslant 0 \\ & h^{B} \left( \Phi_{sr}^{B} \right) = 0, \quad \forall s, \forall r \\ & g^{B} \left( \overline{p}, \Phi_{s}^{D}, \Phi_{sr}^{B}; \rho_{s}, \Delta \rho_{sr} \right) \leqslant 0, \quad \forall s, \forall r \\ & \Phi_{s}^{D} \in \arg \begin{cases} \underset{\Phi_{s}^{D}}{\text{Min}} & \mathcal{C}^{D} \left( \Phi_{s}^{D} \right) \\ \text{s.t.} & h^{D} \left( \Phi_{s}^{D}; l_{s} \right) = 0 \\ & g^{D} \left( \overline{p}, \Phi_{s}^{D}; \rho_{s} \right) \leqslant 0 \end{cases} \forall s. \end{split}$$

Impose cost merit-order at the day-ahead



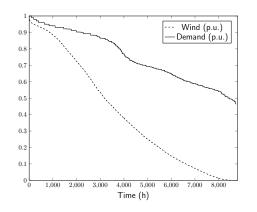
## Data of illustrative example



- Inflexible and cheap generating unit  $(g_1)$
- Inelastic load (l<sub>1</sub>)
- Expansion projects:
  - 1 wind farm  $(\hat{w}_1)$
  - 2 flexible but more expensive units  $(\hat{g}_1, \hat{g}_2)$ . These units have the same fuel cost but  $\hat{q}_2$  provides cheaper downward regulation
  - 3 transmission lines  $(\hat{f}_1, \hat{f}_2, \hat{f}_3)$



## Data of illustrative example



- 20 day-ahead blocks
- 30 balancing scenarios



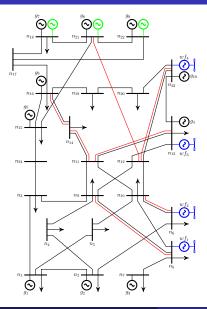
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	No forecast errors	Efficient market	Inefficient market
Cap. $\hat{w}_1$	392	413	441
Cap. $\hat{f}_1$	392	369	377
Cap. $\hat{g}_1/\hat{f}_2$	0	0	195
Cap. $\hat{g}_2/\hat{f}_3$	0	202	0
Inv. cost	20.69	27.15	28.52

- Forecast errors involve higher stochastic power capacity
- Without forecast errors, no investments in flexible generation
- With forecast errors, some investment in flexible generation
- Forecast errors increased the investment costs.
- Investment costs are reduced under efficient market



#### Data of case study



- 24-bus system (IEEE)
- 10 existing conventional units
- 3 flexible generating units
- Variable demand
- 4 projects of stochastic units
- 3 new flexible generating units
- 7 new transmission lines
- Renewable target of 20/30/40%



		No errors	Efficient	Inefficient
	$n_6$	-	-	50
Wind capacity	$n_8$	950	1000	900
	$n_{13}$	-	-	-
	$n_{23}$	400	350	450
	$n_{18}$	-	-	-
Flexible Generation	$n_{21}$	-	80	-
	$n_{22}$	-	-	160
	$n_6 n_{10}$	-	-	-
	$n_8n_9$	-	-	-
	$n_{11}n_{13}$	175	175	175
Line capacity	$n_{11}n_{14}$	-	-	175
	$n_{12}n_{21}$	-	350	-
	$n_{12}n_{23}$	-	-	-
	$n_{14}n_{16}$	-	-	175
Investment cost		162.6	165.1	172.8

#### Consequences of disregarding forecast errors

Renewables target No forecast errors One-stage market Expansion planning (1) Forecast errors Eff./Inef. market Total cost (1) Renewables penetration (1)

Renewables target Forecast errors Eff./Inef. market Expansion planning (2) Total cost (2) Renewables penetration (2)



#### Consequences of disregarding forecast errors

Market	Desired target	Cost increase	Achieved target
Efficient	20%	0.1%	19.2%
	30%	0.5%	26.5%
	40%	-0.3%	31.5%
Inefficient	20%	8.7%	19.3%
	30%	16.2%	28.7%
	40%	19.8%	36.1%

- Efficient market design
  - Similar total costs
  - Renewables penetration below the target
- Inefficient market design
  - Significant increase of total costs
  - Penetration levels closer to the desired target



#### Summary

- We have explained how time variability, long-term and short-term uncertainty can be modeled in G-TEP
- We have presented a set of G-TEP that account for the forecast errors of stochastic production and two different market designs
- These models can be reformulated as single-level mixed-integer linear programming problems
- Considering production forecast errors impacts the generation and transmission expansion planning of a power system
- An efficient market design softens the negative effects of forecast errors and leads to cheaper expansion plans for a given target
- The consequences of an expansion plan determined disregarding forecast errors highly depend on the market design



- Incorporate strategic behaviour of market players
- Modify the models to account for flexibility using unit commitment constraints (ramp rates, minimum times, etc)
- Model intermediate market designs between the paradigmatic efficient and inefficient
- Apply dedicated computational methods to improve tractability of the multi-year case



#### All details can be found in

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#### ABSTRACT

This paper analyzes the impact of production forecast errors on the expansion planning of a power system and investigates the influence of market design to facilitate the integration of renewable generation. For this purpose, we propose a programming modeling framework to determine the generation and transmission expansion plan that minimizes system-wide investment and operating costs, while ensuring a given share of renewable generation in the electricity supply. Unlike existing ones, this framework includes both a day-ahead and a balancing market so as to capture the impact of both production forecasts and the associated prediction errors. Within this framework, we consider two paradigmatic market designs that essentially differ in whether the day-ahead generation schedule and the subsequent balancing re-dispatch are co-optimized or not. The main features and results of the model set-ups are discussed using an illustrative four-node example and a more realistic 24-node case study.

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## Thanks for the attention!

# Questions?

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