Regression Nash Equilibrium in Electricity Market

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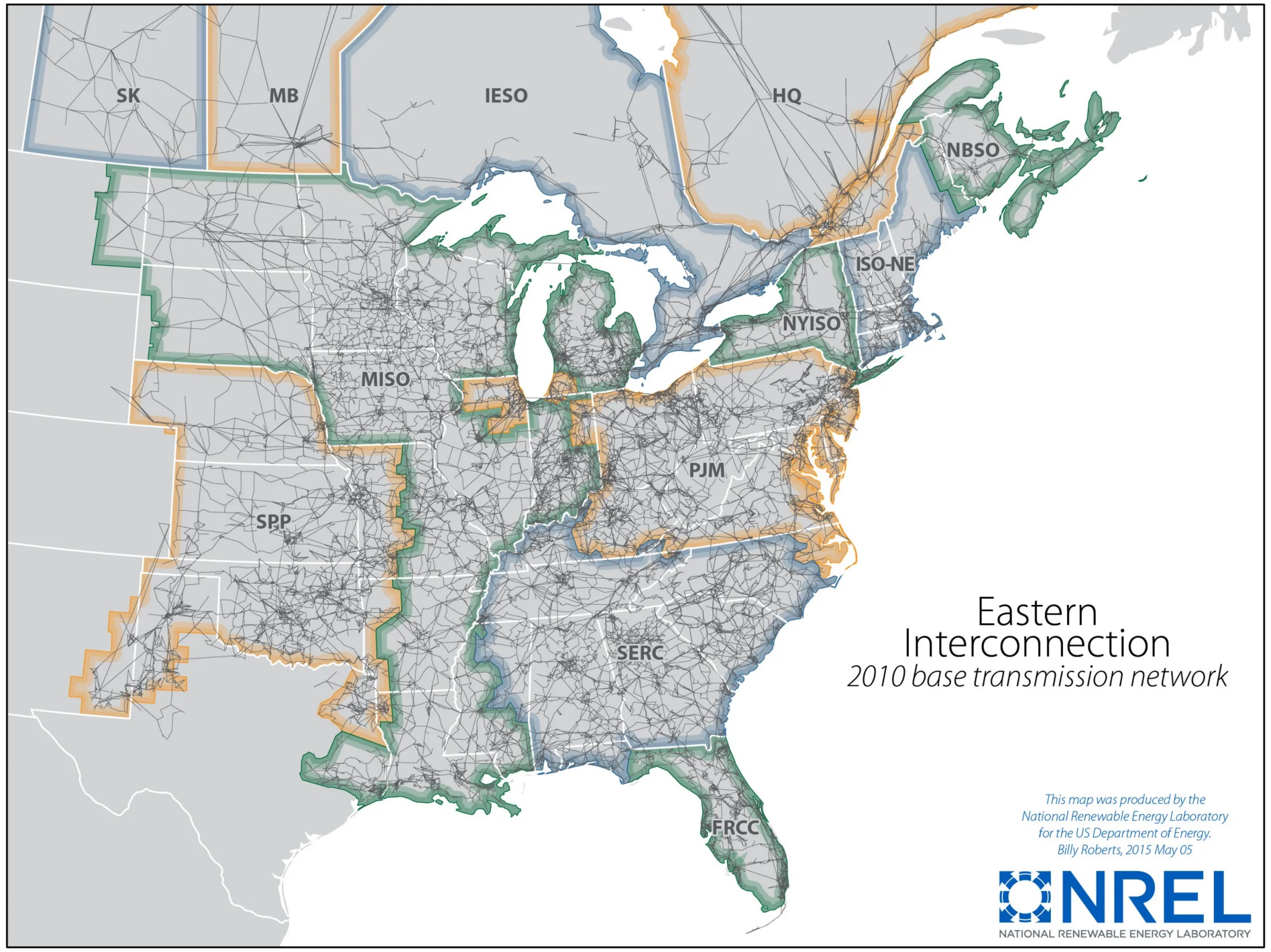
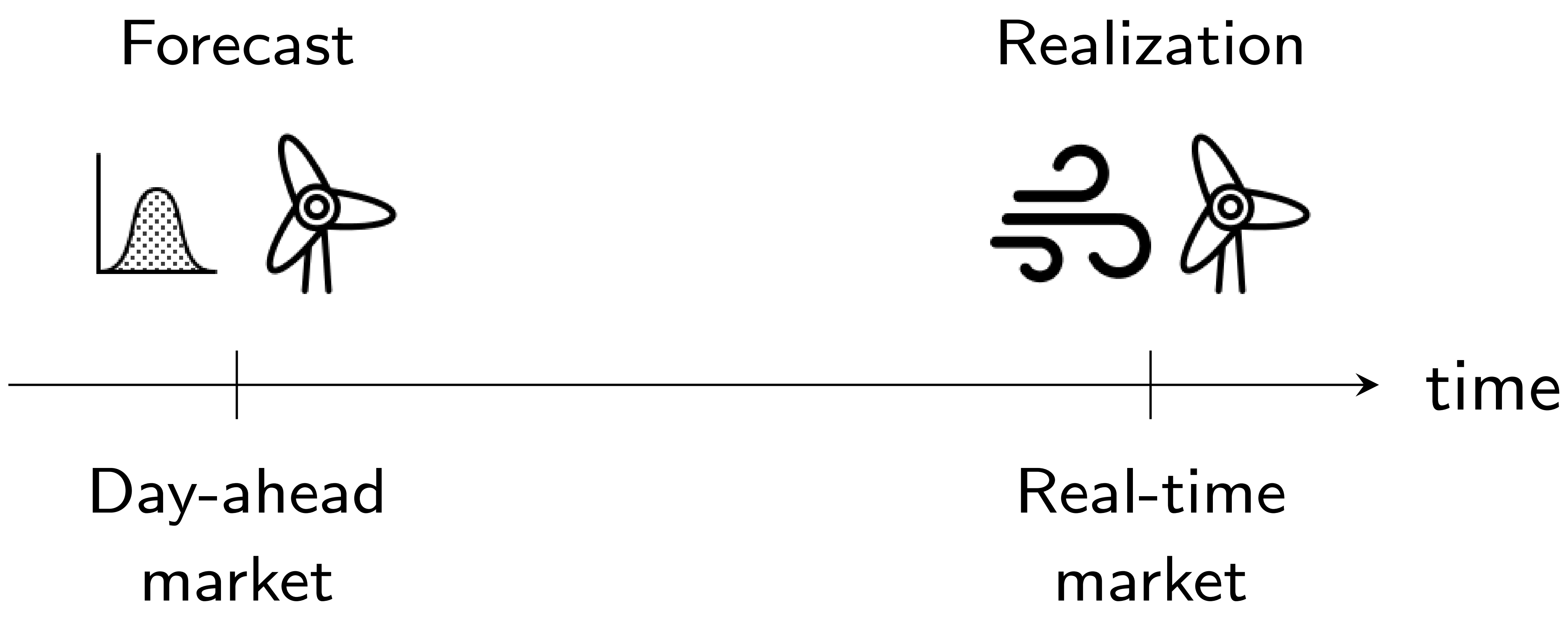
North American power grid



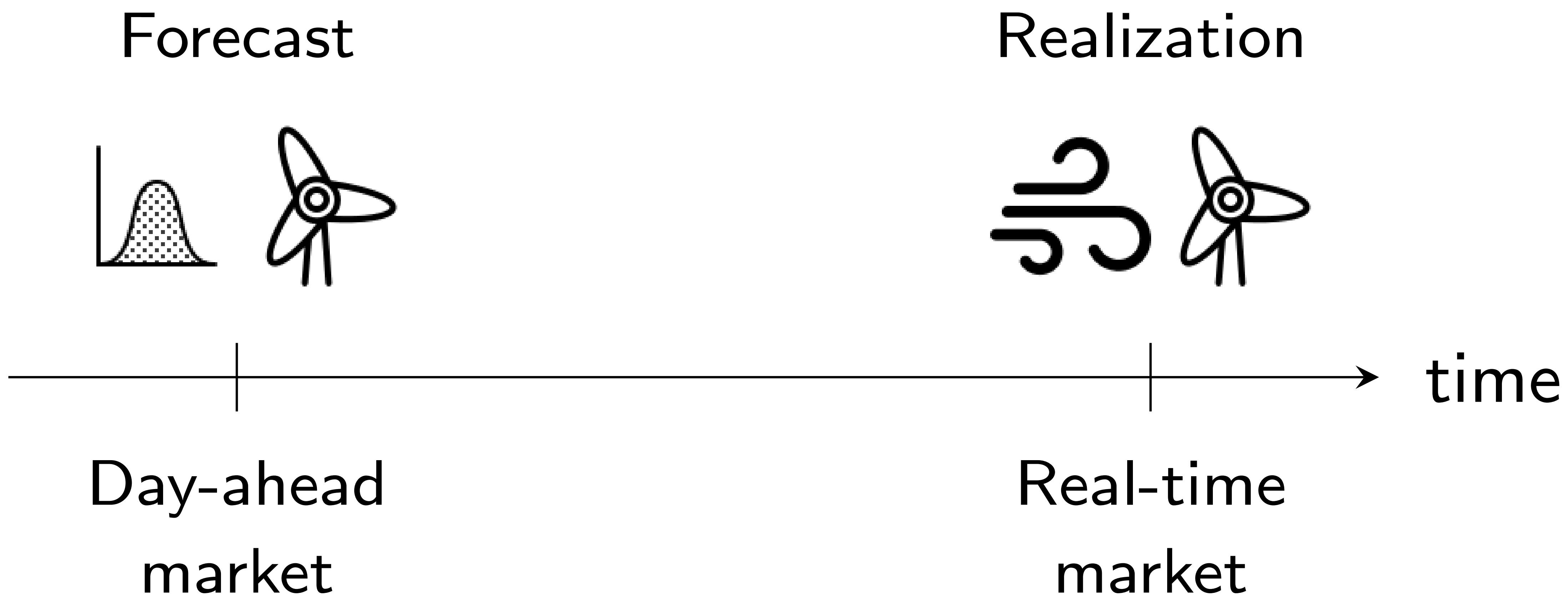
- The world's largest machine
- Mathematical programming (optimization) is a major computational tool for power grids:
  - Operational and long-term planning
  - Electricity market-clearing auctions
  - ED, UC, SCUC, PF, OPF, ...
- What makes electricity such a special commodity?
  - $+$ Homogeneous good with instantaneous delivery
  - $-$ Requires very sophisticated infrastructure
  - $-$ Limited storage capacity $\rightarrow$ balance at all times
  - $\rightarrow$ Only marginal % of electricity is traded in real-time; the majority – well ahead of operations.

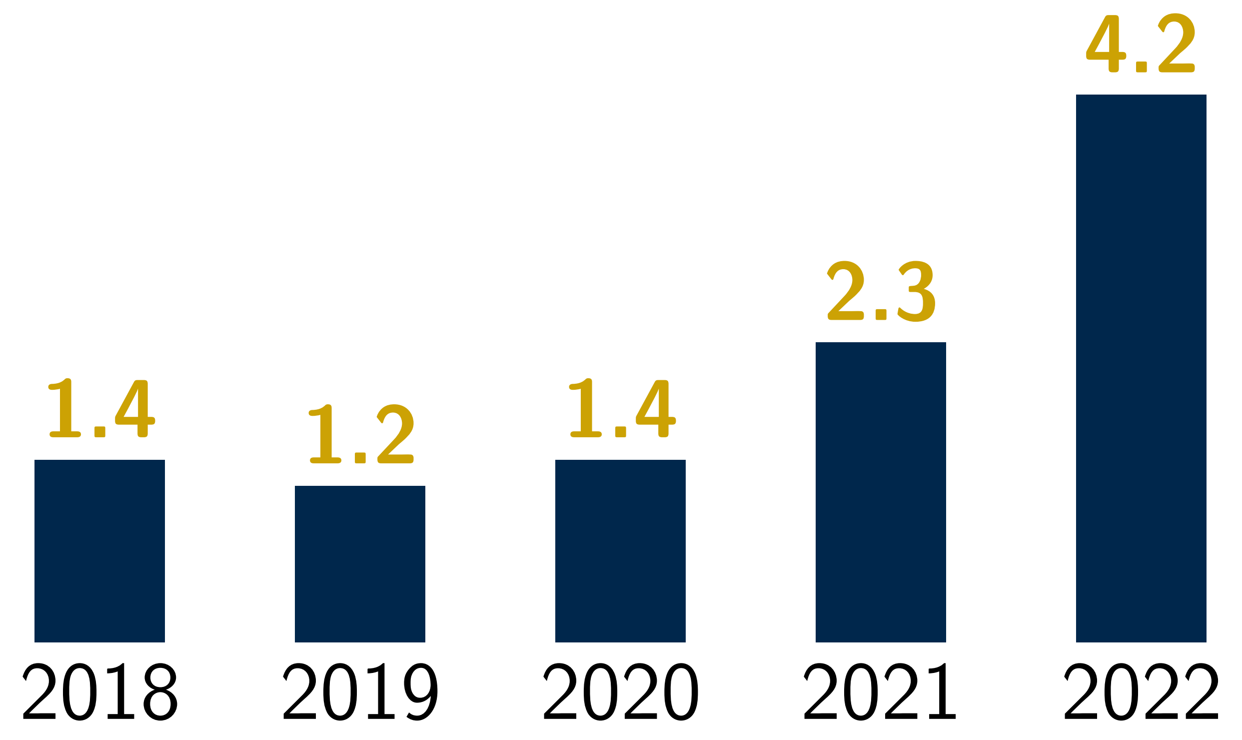
Two-stage electricity markets



- Two-stage electricity markets to manage uncertainty of renewables:
  - Day-ahead market: minimize the cost of power supply w.r.t. forecast
  - Real-time market: least-cost re-dispatch to accommodate forecast errors
- As renewable penetration increases, the cost of real-time re-dispatch also increases

Two-stage electricity markets





Re-dispatch cost in Germany [Bn €]

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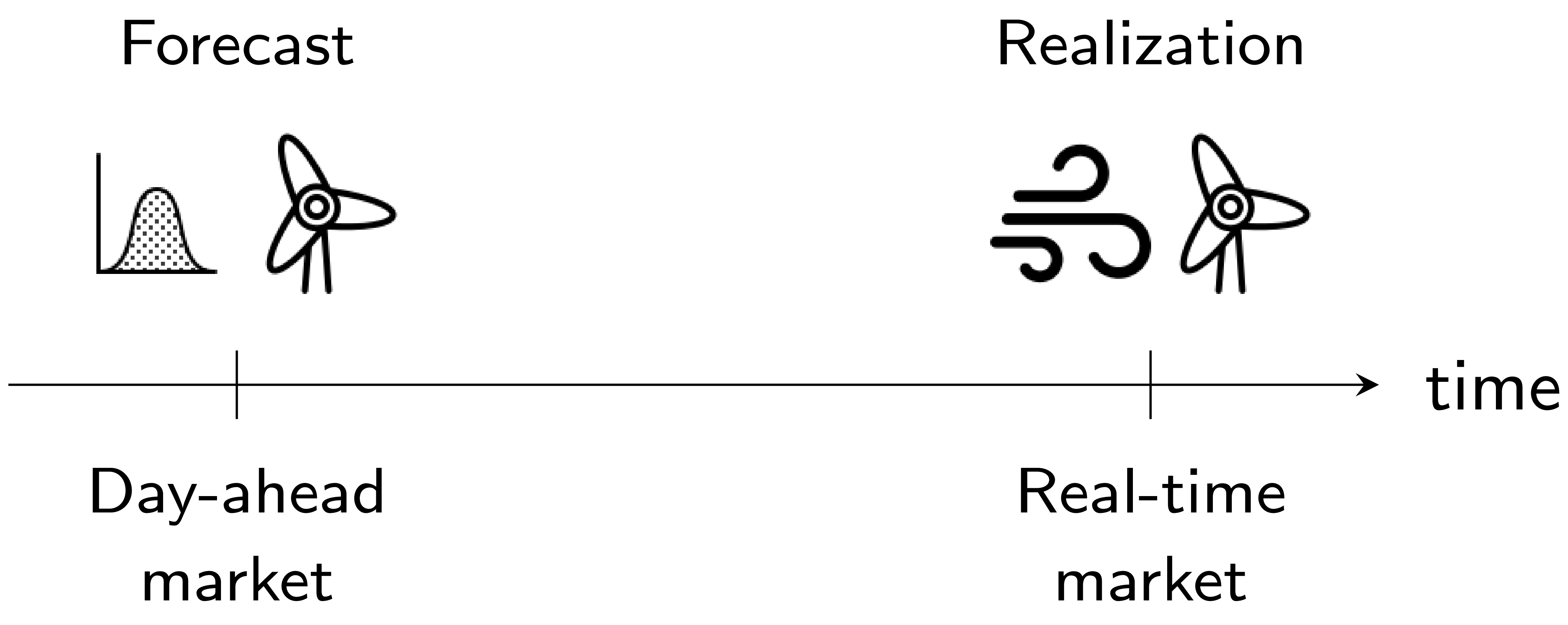

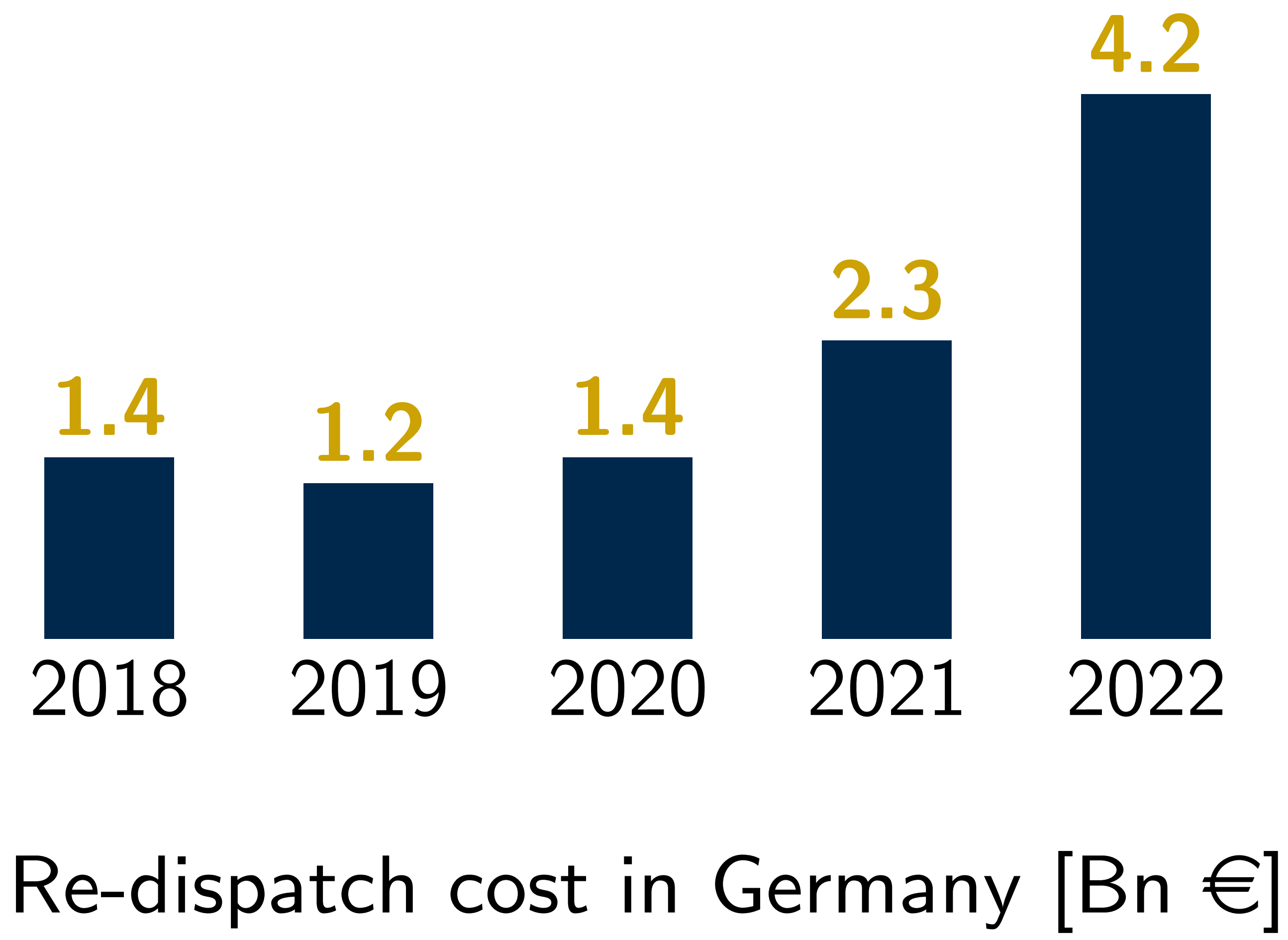

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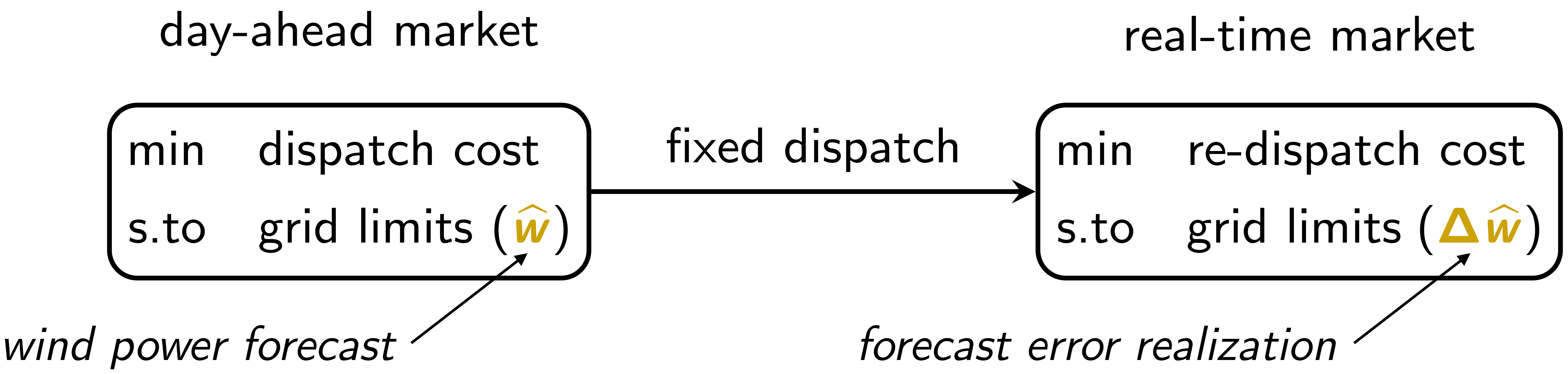
How to make renewable power generation less expensive for the system?

Two-stage electricity markets (continued)



Two-stage electricity markets (continued)

day-ahead market

min dispatch cost
s.to grid limits ($\widehat{w}$)

wind power forecast

→ fixed dispatch →

real-time market

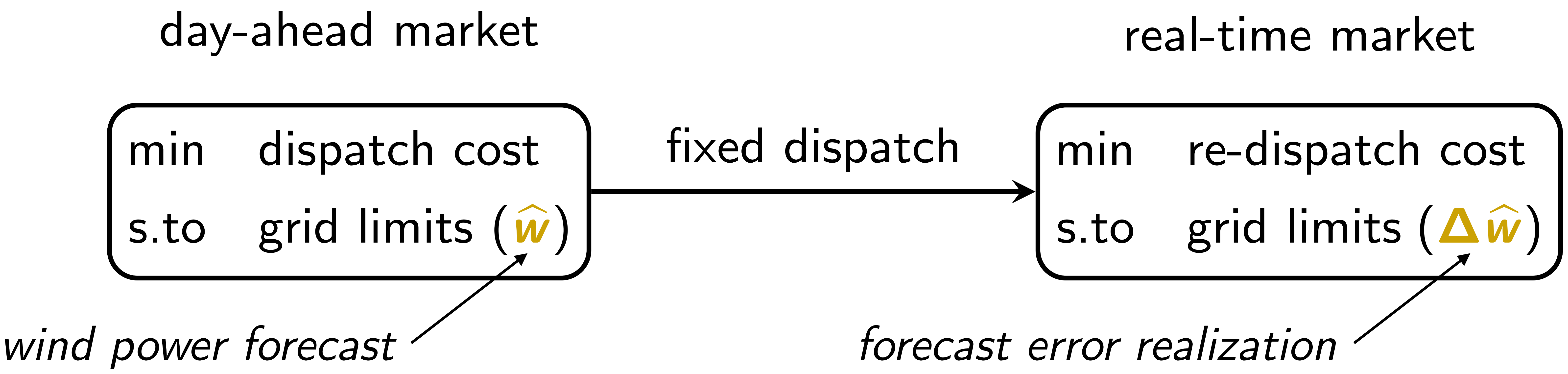
min re-dispatch cost
s.to grid limits ($\Delta\widehat{w}$)

forecast error realization

Improving cost efficiency across day-ahead and real-time markets:

- Stochastic electricity market design [PZP10, M+12, Dvo19]:
  - + Co-optimization of dispatch and re-dispatch decisions
  - + Least-cost solution in *expectation*
  - – Market properties only hold in *expectation*

$$\begin{aligned} \min \quad & \text{dispatch cost} + \mathbb{E}_{\mathbb{P}_{\Delta\widehat{w}}}[\text{re-dispatch cost}] \\ \text{s.to} \quad & \text{grid limits } (\widehat{w}, \Delta\widehat{w}) \text{ for all } \Delta\widehat{w} \sim \mathbb{P}_{\Delta\widehat{w}} \end{aligned}$$



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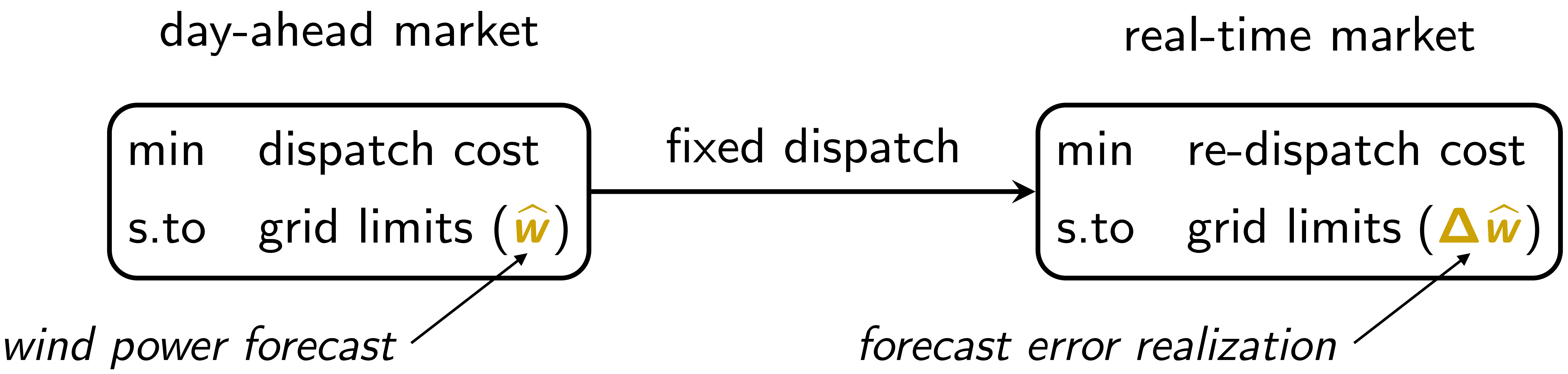
- Approximating stochastic market efficiency within deterministic markets:
  - Improved scheduling of renewbales [M+14]
  - Cost-aware reserve requirements [DDM18]
  - Cost-aware transmission allocation [JKP17, DP19]

Two-stage electricity markets (continued)



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In our work, we follow this path with focused on advanced data analytics (machine learning)

Power systems optimization meets machine learning (ML)

Typical grid optimization problem:

$$\begin{aligned} \min_{\mathbf{p},\mathbf{q},\mathbf{u}} \quad & c(\mathbf{p}_\theta) + s(\mathbf{u}_\theta) && \textit{generation and UC cost} \\ \text{s.to} \quad & f(\mathbf{p}_\theta, \mathbf{q}_\theta, \mathbf{w}_\theta) = \mathbf{0} \quad : \boldsymbol{\lambda}_\theta && \textit{power flow equations} \\ & g(\mathbf{p}_\theta, \mathbf{q}_\theta, \mathbf{w}_\theta) \leqslant b(\mathbf{u}_\theta) && \textit{gen, flow, voltage limits} \end{aligned}$$

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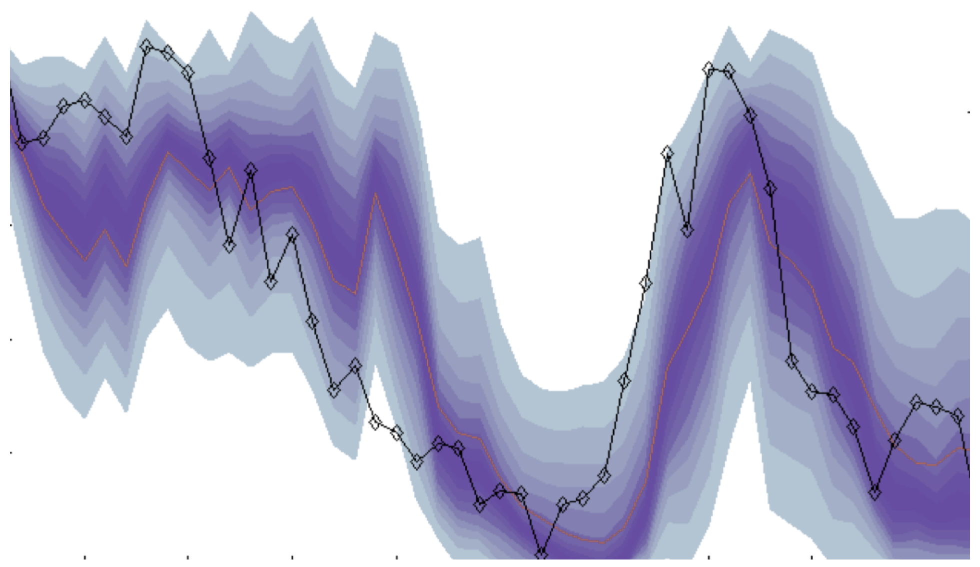
Net load forecasting [PCK07, ZHS24]



Forecast minimizing the cost of re-dispatch

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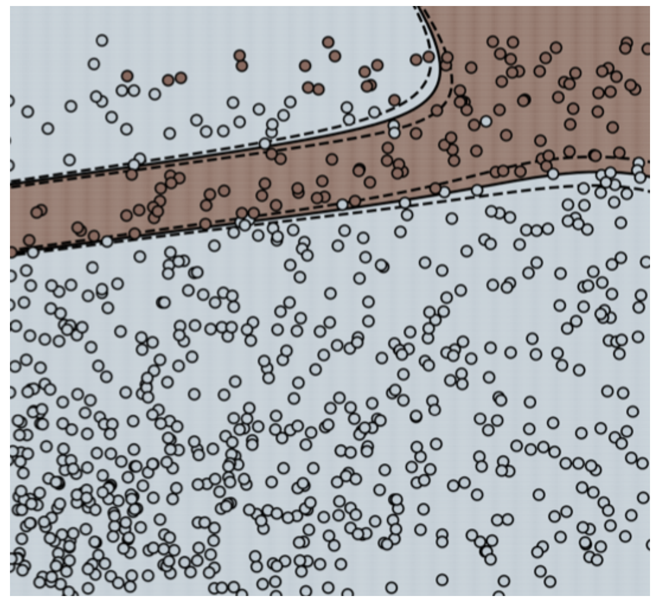
SVM-based prediction of on/off gen. status [PK24]

Efficient warm start for MIP solvers



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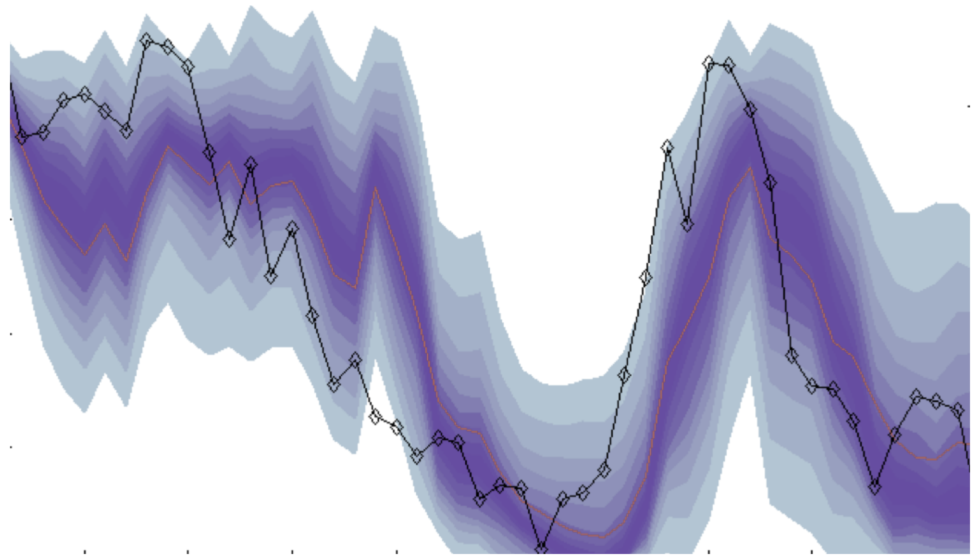

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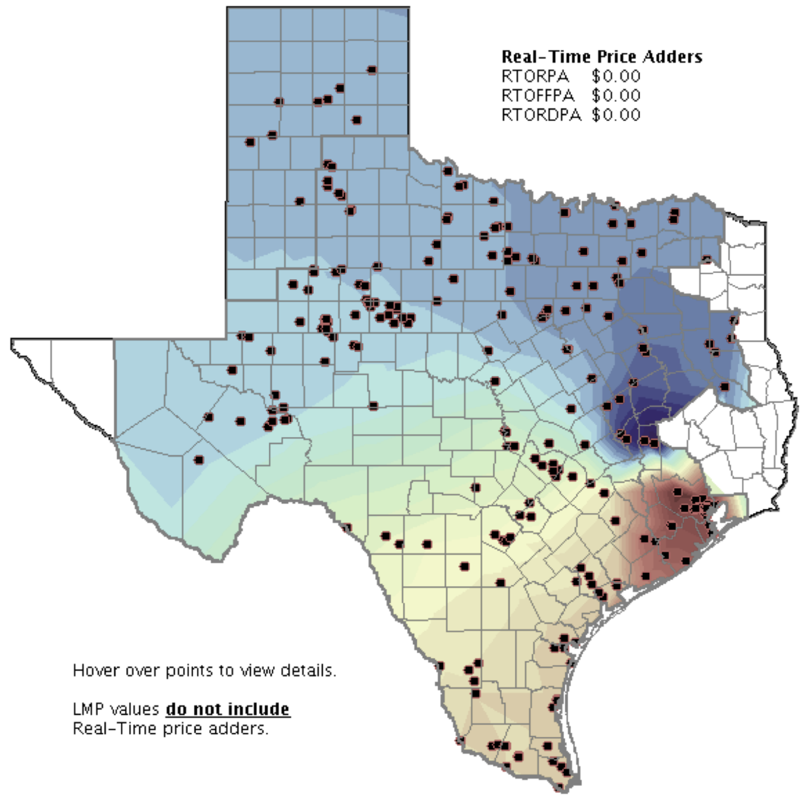
Real-time electricity pricing via GNNs [LWZ21]

Real-time pricing at ultrafast time scales



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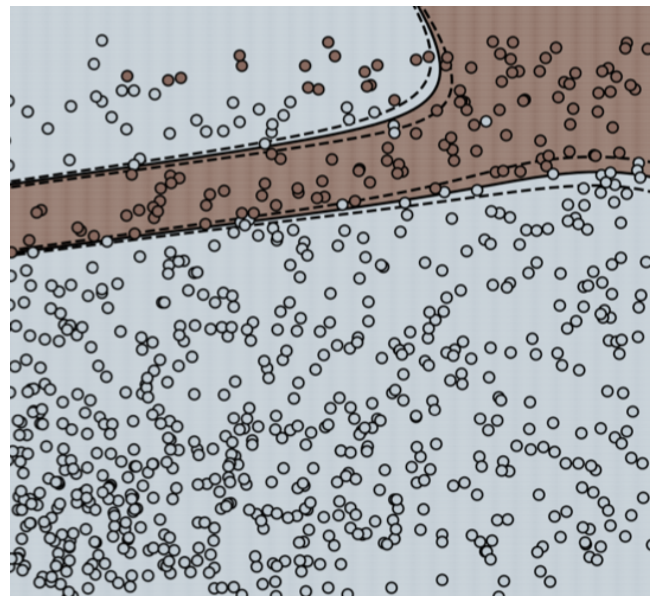

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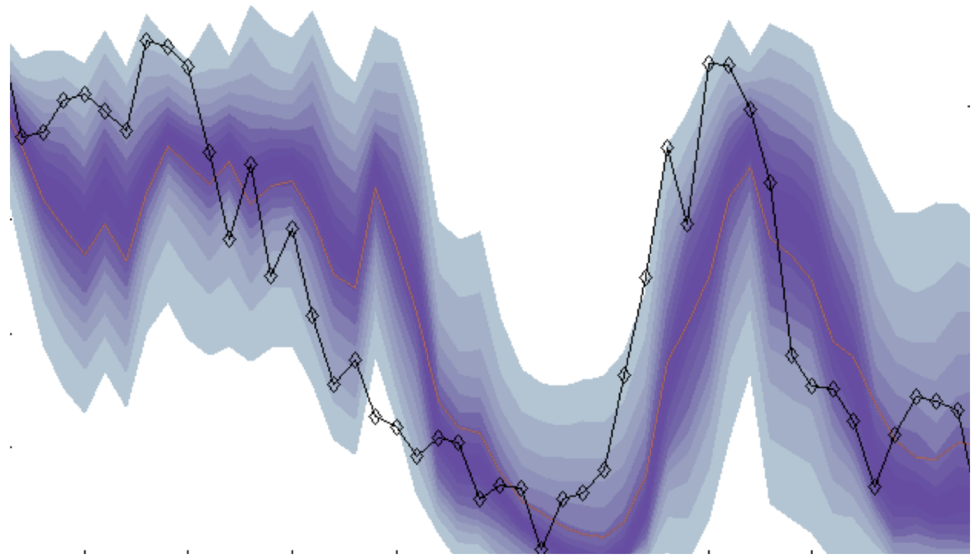

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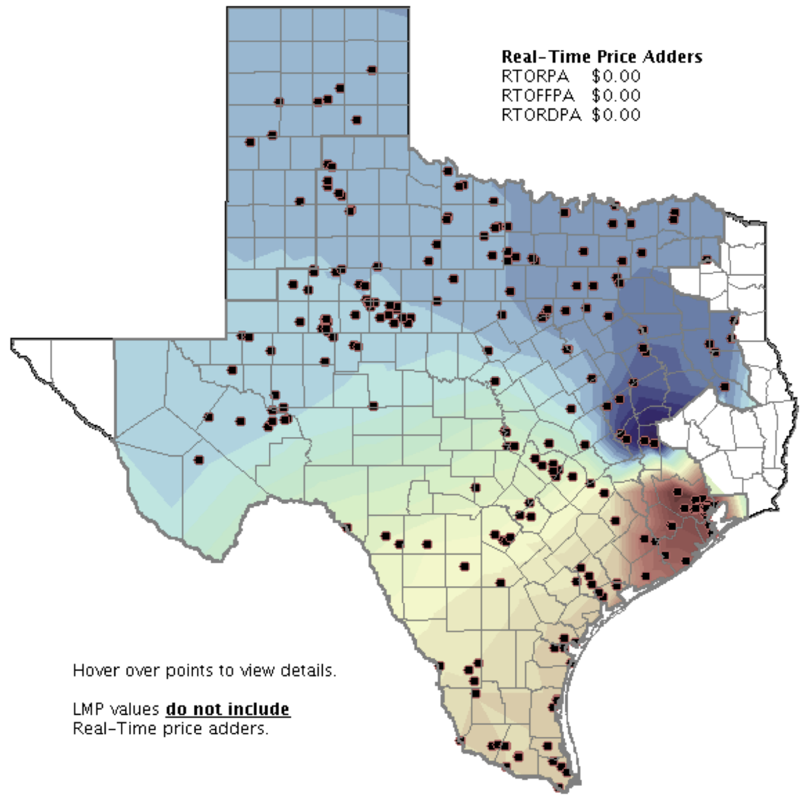

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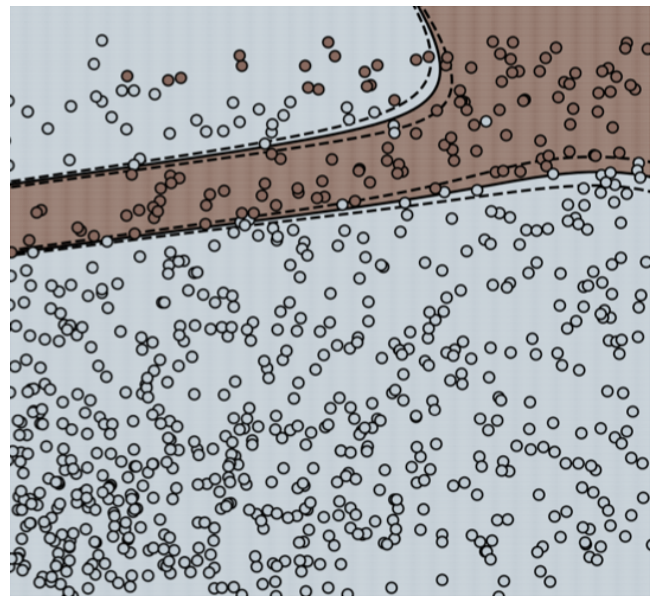
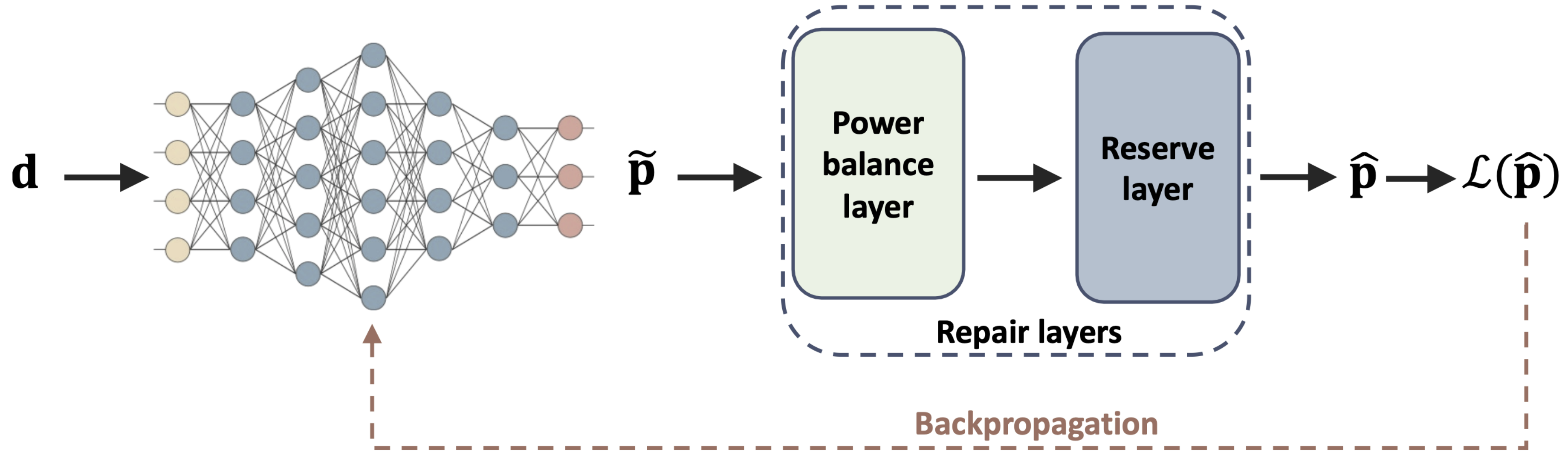
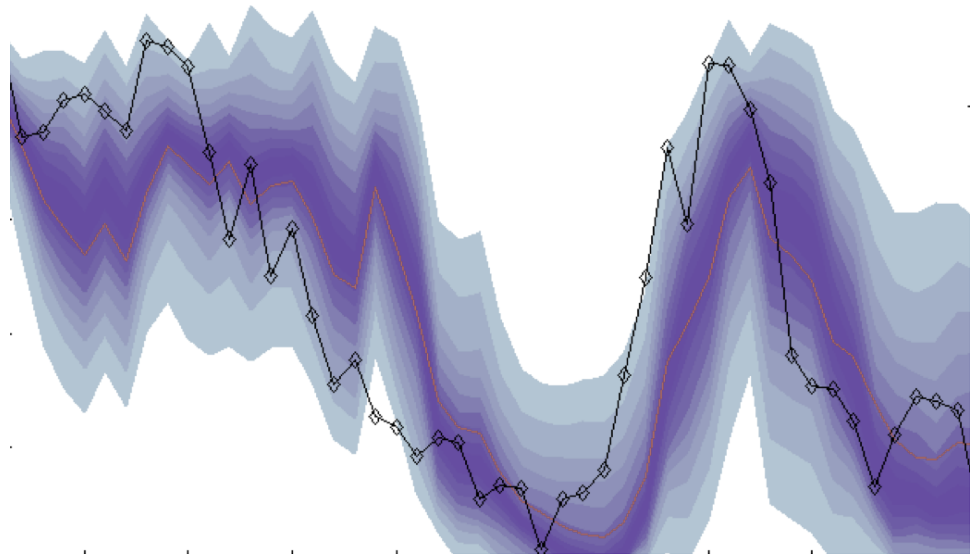


Optimal generation dispatch prediction using optimization proxies [CTVH23]



Extremely fast contingency screening

Net load forecasting [PCK07, ZHS24]



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This talk is on the dual role of machine learning in grid operations:

- Significant speed up and reported efficiency gains
  - Assisting decisions on ultrafast time scale
  - Approximates the efficiency of stochastic market design
- Imperfect predictions often lead to decision errors
  - Minimizing the impact of ML errors on pricing and dispatch decisions
  - Achieving equilibrium among ML models applied to grid optimization

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  - Achieving equilibrium among ML models applied to grid optimization —— Part II

Agenda

Introduction

Controlling the impact of ML errors on electricity pricing

Nash equilibrium of ML models in electricity markets

Concluding remarks

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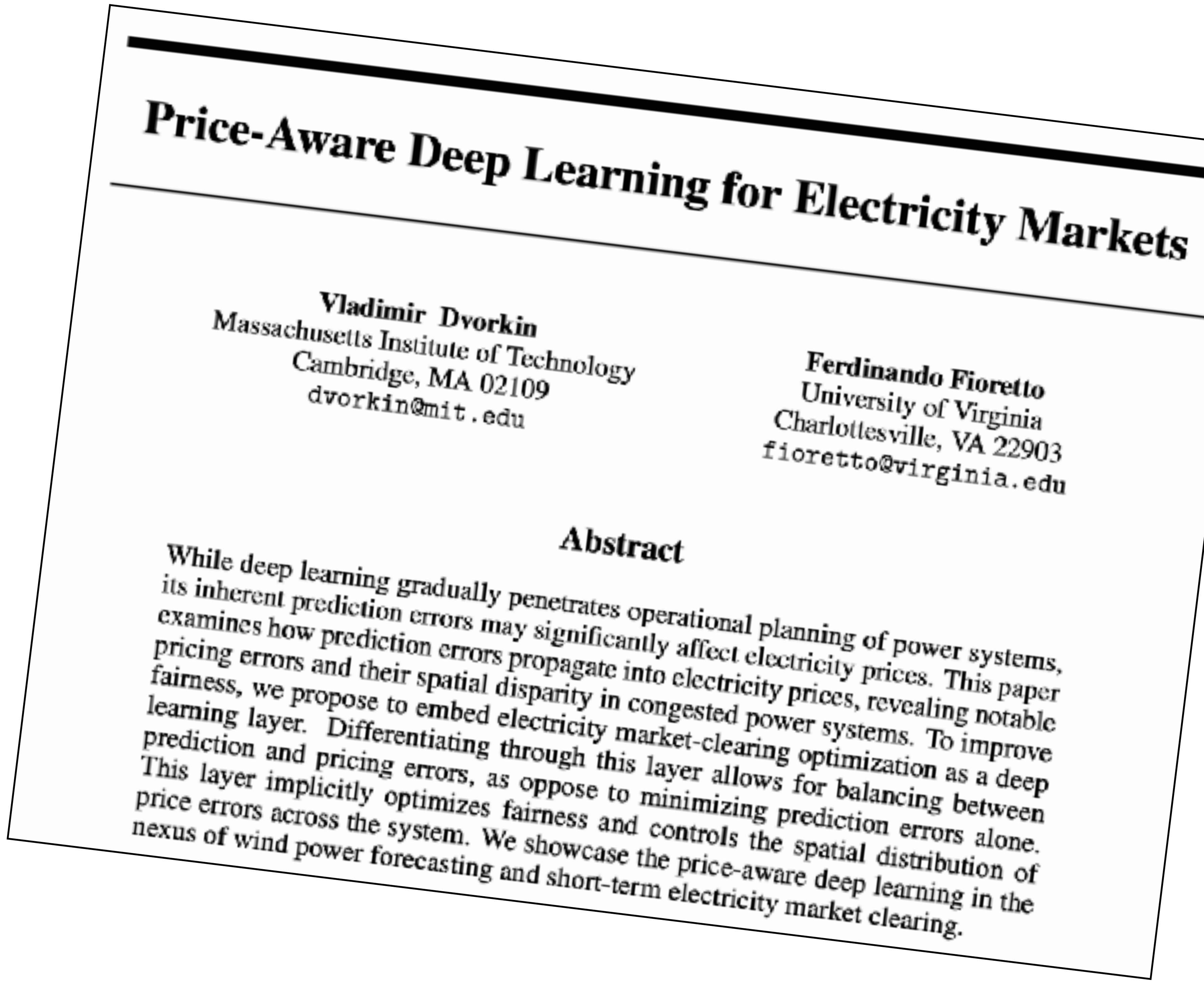

Price-Aware Deep Learning for Electricity Markets

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Abstract

While deep learning gradually penetrates operational planning of power systems, its inherent prediction errors may significantly affect electricity prices. This paper examines how prediction errors propagate into electricity prices, revealing notable pricing errors and their spatial disparity in congested power systems. To improve fairness, we propose to embed electricity market-clearing optimization as a deep learning layer. Differentiating through this layer allows for balancing between prediction and pricing errors, as oppose to minimizing prediction errors alone. This layer implicitly optimizes fairness and controls the spatial distribution of price errors across the system. We showcase the price-aware deep learning in the nexus of wind power forecasting and short-term electricity market clearing.

DC optimal power flow:

$$\min_{\underline{\mathbf{p}}\leqslant\mathbf{p}\leqslant\overline{\mathbf{p}}} \quad \mathbf{p}^\top\mathbf{C}\mathbf{p}+\mathbf{c}^\top\mathbf{p}$$

$$\text{s.to} \quad \mathbf{1}^\top(\mathbf{p}+\widehat{\mathbf{w}}-\mathbf{d})=\mathbf{0} \;:\; \lambda_b$$

$$|\mathbf{F}(\mathbf{p}+\widehat{\mathbf{w}}-\mathbf{d})|\leqslant\overline{\mathbf{f}} \;:\; \boldsymbol{\lambda}_{\overline{f}},\boldsymbol{\lambda}_{\underline{f}}$$

Locational marginal prices:

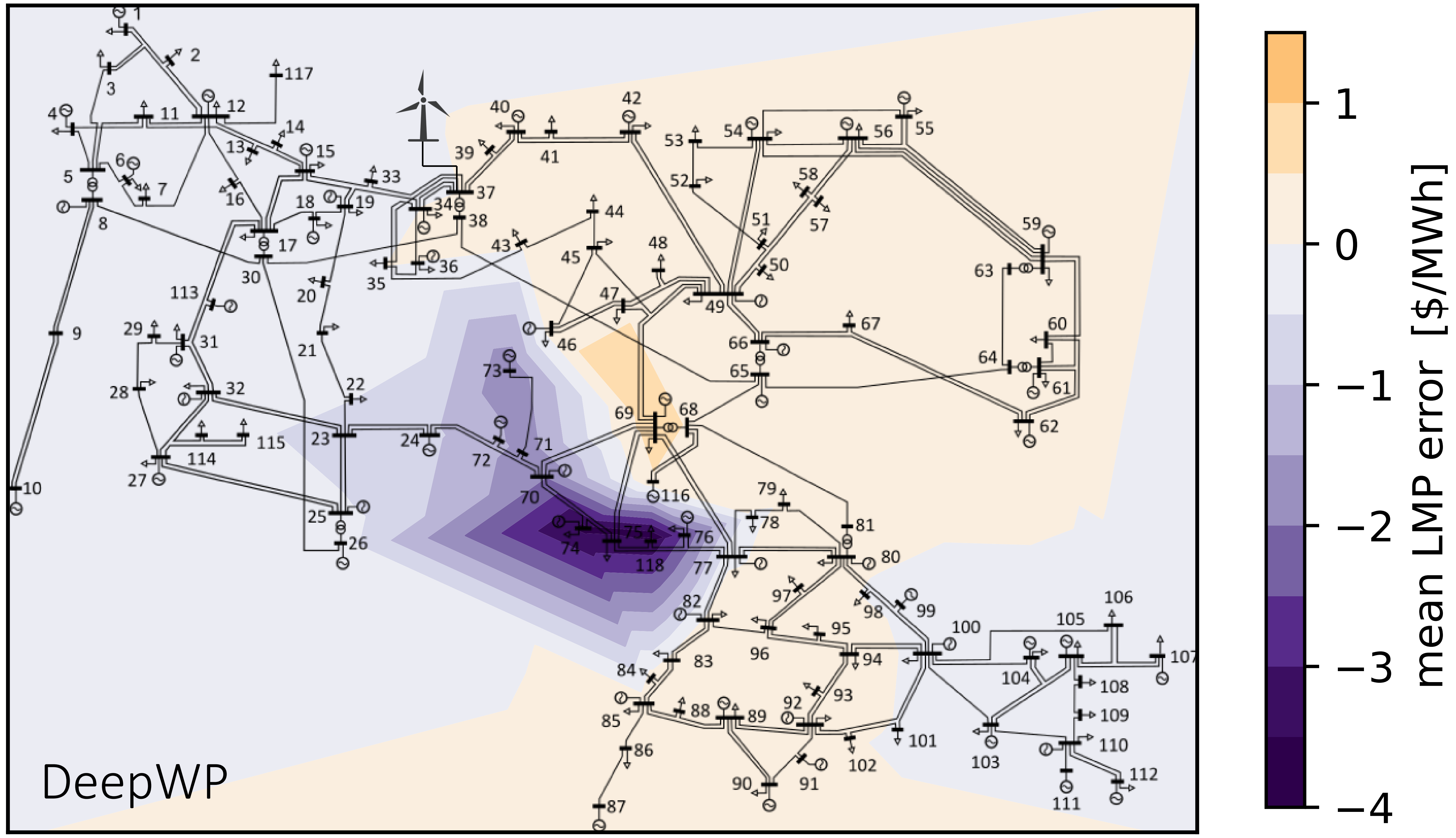
$$\boldsymbol{\lambda}(\widehat{\mathbf{w}})=\underbrace{\mathbf{1}\cdot\lambda_b(\widehat{\mathbf{w}})}_{\text{uniform part}}-\underbrace{\mathbf{F}^\top(\boldsymbol{\lambda}_{\overline{f}}(\widehat{\mathbf{w}})-\boldsymbol{\lambda}_{\underline{f}}(\widehat{\mathbf{w}}))}_{\text{congestion part}}$$

- Electricity market clearing based on DC-OPF
- Relies on the *forecast* $\widehat{\mathbf{w}}$ of wind power generation
- Forecast errors → pricing errors via market optimization
- May not be a dominant generation resource, yet still exposes the entire electricity trading to errors

ML errors = decision errors

DC optimal power flow:

$$\begin{aligned} \min_{\underline{\mathbf{p}}\leqslant\mathbf{p}\leqslant\overline{\mathbf{p}}}\quad & \mathbf{p}^\top \mathbf{C}\mathbf{p} + \mathbf{c}^\top \mathbf{p} \\ \text{s.to}\quad & \mathbf{1}^\top(\mathbf{p} + \widehat{\mathbf{w}} - \mathbf{d}) = \mathbf{0} \;:\; \lambda_b \\ & |\mathbf{F}(\mathbf{p} + \widehat{\mathbf{w}} - \mathbf{d})| \leqslant \overline{\mathbf{f}} \;:\; \boldsymbol{\lambda}_{\overline{f}}, \boldsymbol{\lambda}_{\underline{f}} \end{aligned}$$



Locational marginal prices:

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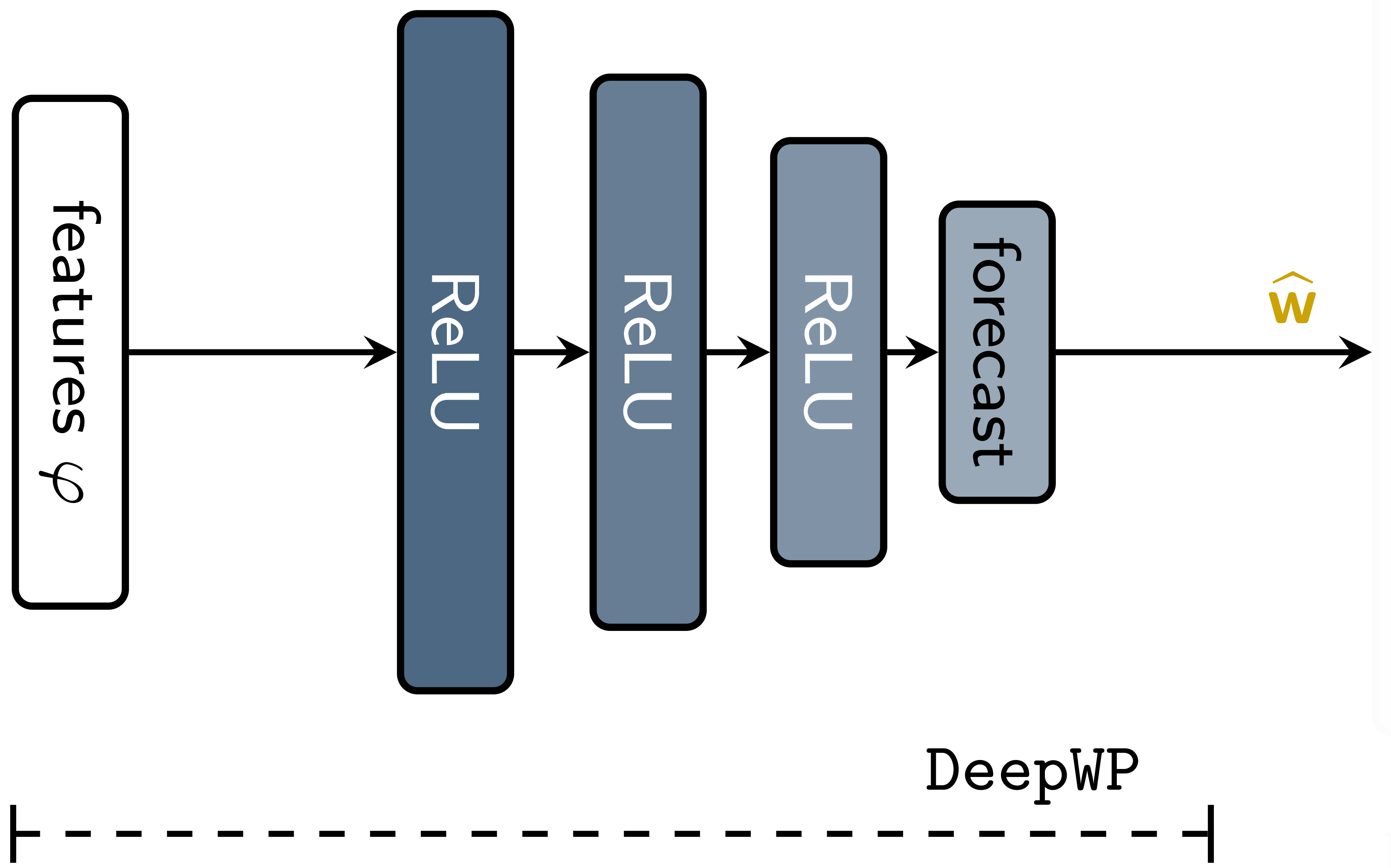
Forecast errors from a single wind power plant propagate into locational marginal price (LMP) errors across the IEEE 118-Bus RTS. Electricity at certain buses is systematically over- or under-priced [DF23].

Market clearing as a deep learning layer

- Dataset $\{(\varphi_1, \mathbf{w}_1), \dots, (\varphi_m, \mathbf{w}_m)\}$ of wind power records, with features φ and measurements $\mathbf{w}$
- Two deep learning architectures `DeepWP` and `DeepWP+` for wind power forecasting:

loss function: $\|\widehat{\mathbf{w}} - \mathbf{w}\|_2^2$



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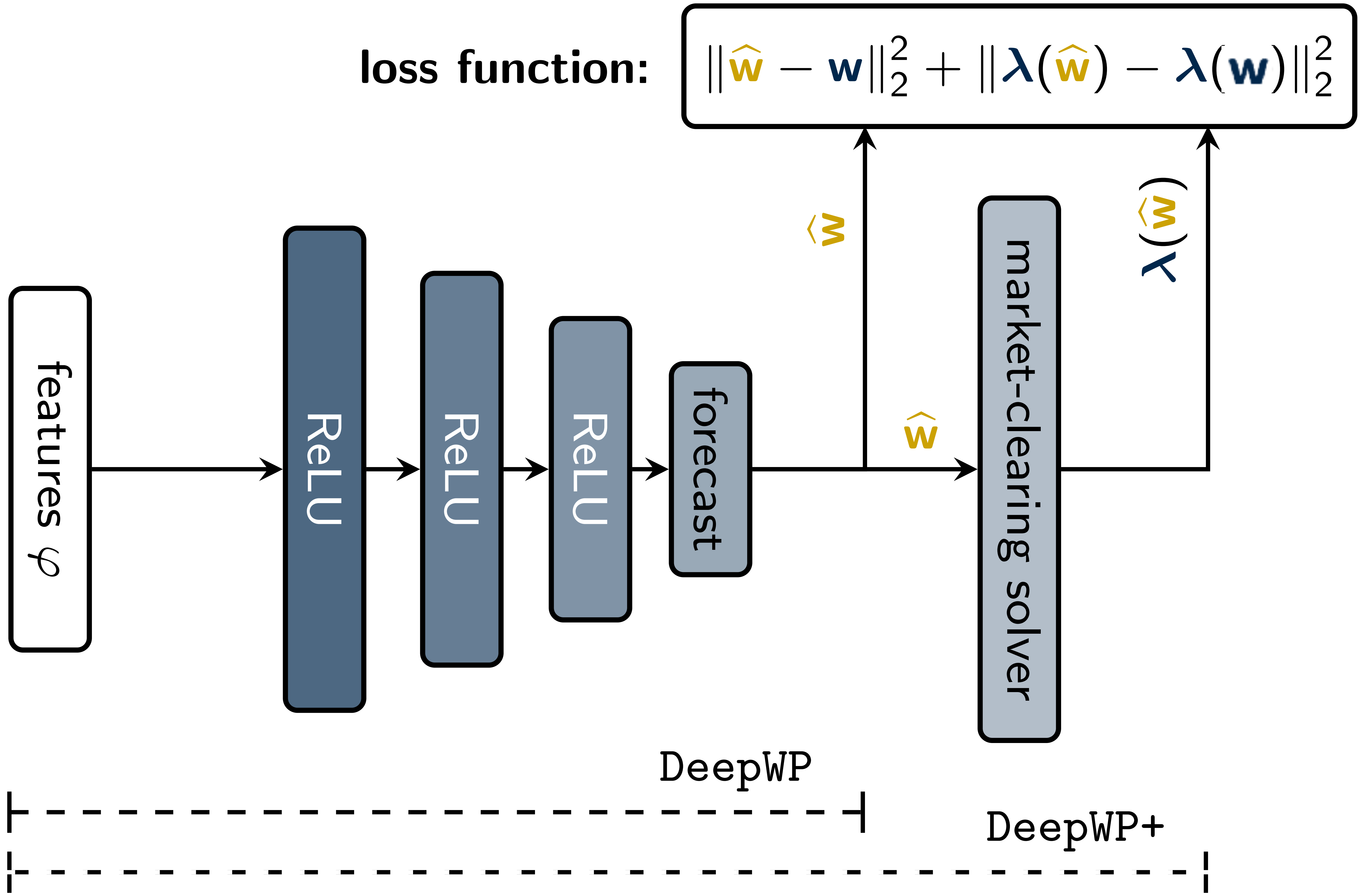

- DeepWP+ incorporates market clearing as an optimization layer [AK17], which informs on pricing errors

- Market-clearing optimization layer significantly slows down the training
- Thousands of market-clearing problems are solved at each training epoch
- We use QP duality and fast distributed algorithms to speed up the process

Market-clearing optimization

$$\begin{aligned} \min_{\underline{\mathbf{p}} \leqslant \mathbf{p} \leqslant \overline{\mathbf{p}}} \quad & \mathbf{p}^\top \mathbf{C}\mathbf{p} + \mathbf{c}^\top \mathbf{p} \\ \text{s.to} \quad & \mathbf{1}^\top(\mathbf{p} + \widehat{\mathbf{w}} - \mathbf{d}) = 0 \\ & |\mathbf{F}(\mathbf{p} + \widehat{\mathbf{w}} - \mathbf{d})| \leqslant \overline{\mathbf{f}} \end{aligned}$$

large constrained optimization

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Market-clearing optimization $\Longrightarrow$ **Equivalent primal form**

$$\min_{\underline{\mathbf{p}}\leqslant\mathbf{p}\leqslant\overline{\mathbf{p}}} \quad \mathbf{p}^\top\mathbf{C}\mathbf{p}+\mathbf{c}^\top\mathbf{p}$$
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$$\min_{\underline{\mathbf{p}}\leqslant\mathbf{p}\leqslant\overline{\mathbf{p}}} \quad \mathbf{p}^\top\mathbf{C}\mathbf{p}+\mathbf{c}^\top\mathbf{p}$$
$$\text{s.to} \quad \mathbf{A}\mathbf{p}\geqslant\mathbf{b}(\widehat{\mathbf{w}}) \;:\; \boldsymbol{\lambda}$$

only inequality constraints

Accelerating market-clearing optimization layer

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Market-clearing optimization $\Longrightarrow$ **Equivalent primal form** $\Longrightarrow$ **Equivalent dual form**

Market-clearing optimization:

$$\begin{aligned} \min_{\underline{p} \leqslant p \leqslant \overline{p}} \quad & p^\top C p + c^\top p \\ \text{s.to} \quad & 1^\top (p + \widehat{w} - d) = 0 \\ & |F(p + \widehat{w} - d)| \leqslant \overline{f} \end{aligned}$$

large constrained optimization

Equivalent primal form:

$$\begin{aligned} \min_{\underline{p} \leqslant p \leqslant \overline{p}} \quad & p^\top C p + c^\top p \\ \text{s.to} \quad & Ap \geqslant b(\widehat{w}) \; : \; \lambda \end{aligned}$$

only inequality constraints

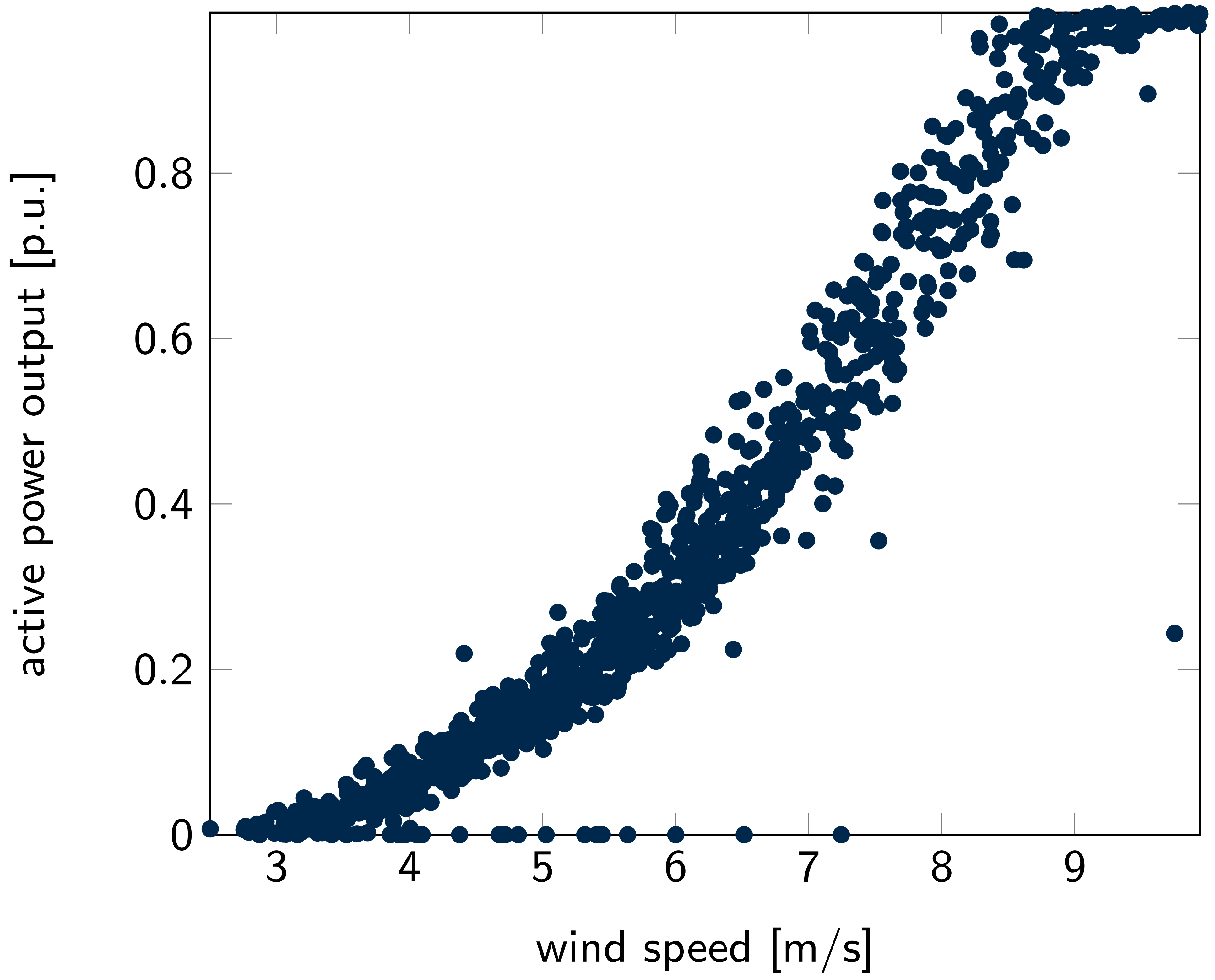
Equivalent dual form:

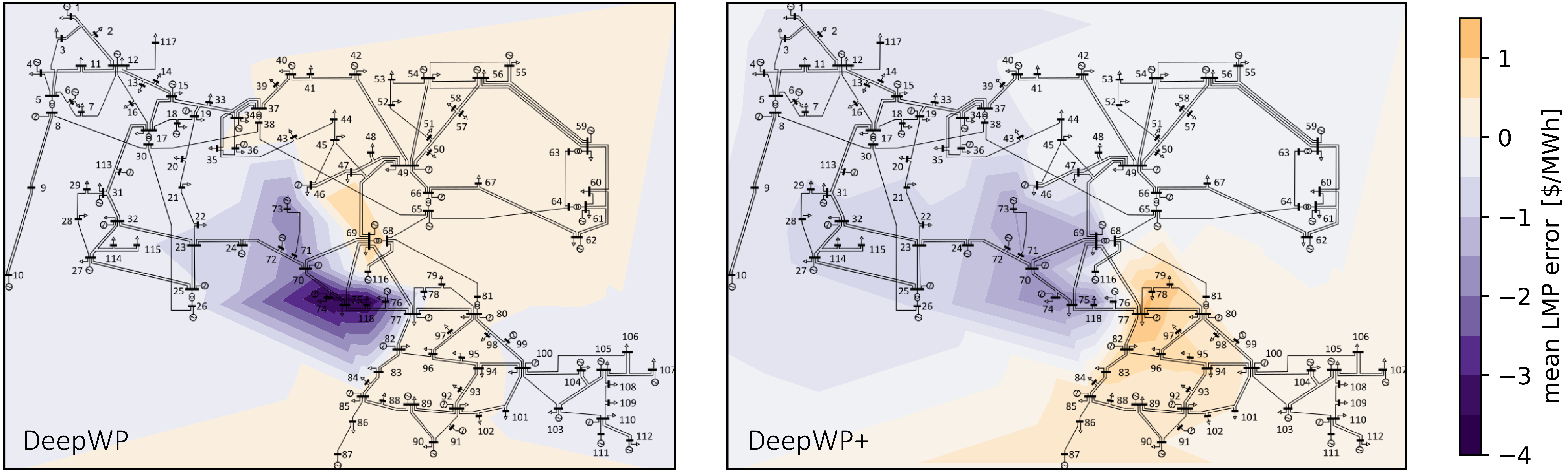
$$\max_{\lambda \geqslant 0} \quad \left(AC^{-1}c + b(\widehat{w})\right)^\top \lambda - \lambda^\top A C^{-1} A^\top \lambda$$

only non-negativity constraints

amenable to fast proximal and ADMM-like algorithms

- 1,000 wind power records from a real wind power turbine:
  - Active power output
  - Wind speed and direction
  - Blade pitch angle
- `DeepWP` has 4 hidden layers with 30 neurons each. `DeepWP+` additionally includes an opt. layer
- ADAM optimizer with varying learning rate

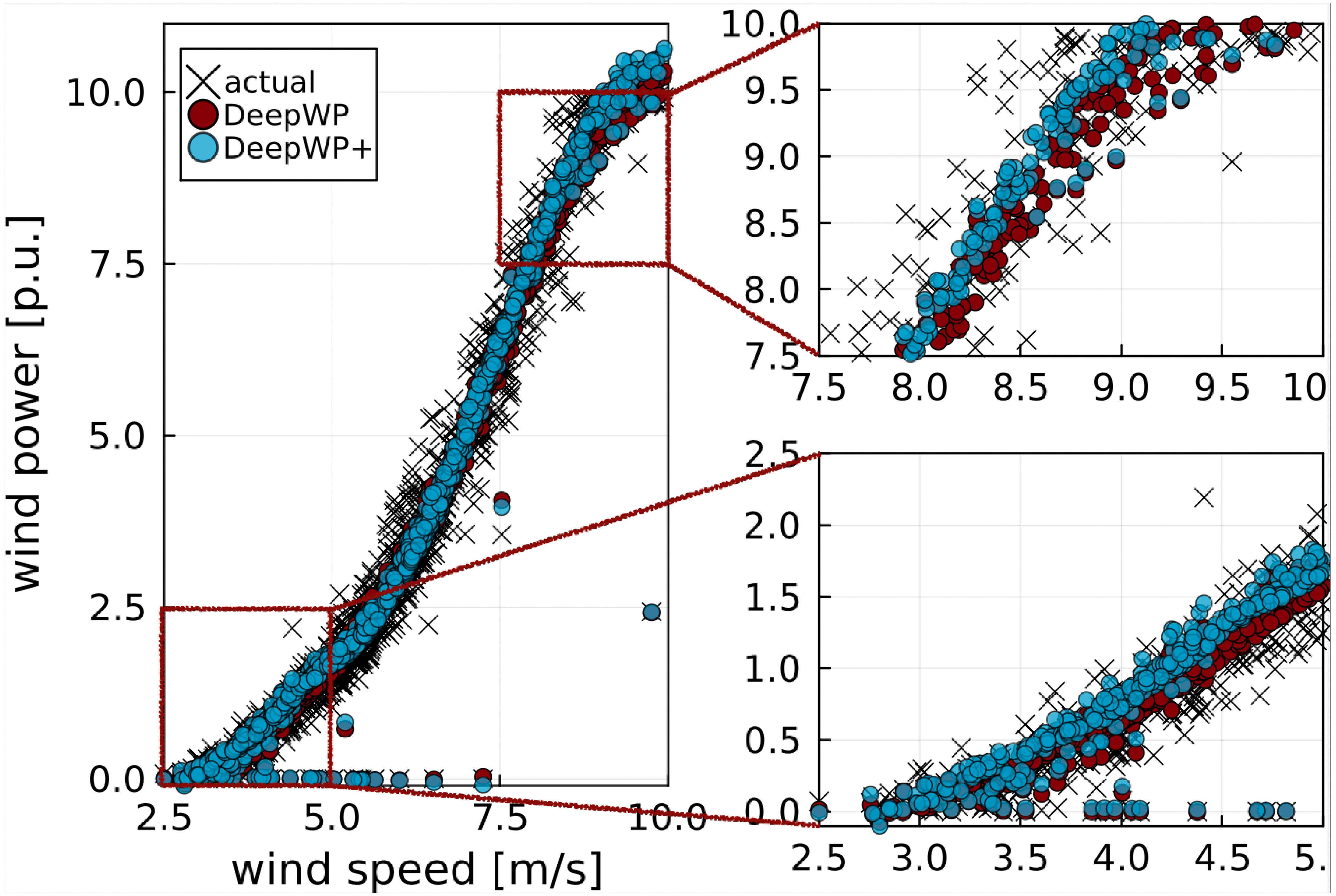




`DeepWP`: Forecast error objective – LMP errors $[-4, 1]$ \$/MWh

`DeepWP+`: LMP error objective – LMP errors $[-1, 1]$ \$/MWh

Wind power forecasts



`DeepWP`: Minimizes the average forecast deviation

`DeepWP+`: Intentionally over-predicts in certain range of wind speeds

Underlying trade-offs between forecast and price errors

case	DeepWP			DeepWP+					
	RMSE($\widehat{\mathbf{w}}$)	RMSE($\widehat{\lambda}$)	CVaR($\widehat{\lambda}$)	RMSE($\widehat{\mathbf{w}}$)		RMSE($\widehat{\lambda}$)		CVaR($\widehat{\lambda}$)	
	MWh	\$/MWh	\$/MWh	MWh	gain	\$/MWh	gain	\$/MWh	gain
14_ieee	0.35	0.62	1.52	0.35	+0.6%	0.61	−0.6%	1.50	−0.8%
57_ieee	2.31	11.03	34.64	2.60	+11.2%	10.72	−2.9%	33.59	−3.1%
24_ieee	4.08	8.62	37.70	4.51	+9.6%	8.33	−3.5%	36.35	−3.7%
39_epri	5.94	11.15	31.21	6.43	+7.6%	10.19	−9.4%	28.02	−11.4%
73_ieee	4.02	5.12	16.21	5.51	+26.9%	4.24	−20.8%	13.41	−20.9%
118_ieee	2.29	3.59	11.32	2.60	+12.1%	2.88	−24.7%	9.06	−25.0%

- Price errors reduction comes at the expense of forecast error
- Price error reduction is more significant in larger networks

For more results, including **price fairness**: https://arxiv.org/pdf/2308.01436

Underlying trade-offs between forecast and price errors

case	DeepWP			DeepWP+					
	RMSE($\widehat{\mathbf{w}}$)	RMSE($\widehat{\boldsymbol{\lambda}}$)	CVaR($\widehat{\boldsymbol{\lambda}}$)	RMSE($\widehat{\mathbf{w}}$)		RMSE($\widehat{\boldsymbol{\lambda}}$)		CVaR($\widehat{\boldsymbol{\lambda}}$)	
	MWh	\$/MWh	\$/MWh	MWh	gain	\$/MWh	gain	\$/MWh	gain
14_ieee	0.35	0.62	1.52	0.35	+0.6%	0.61	−0.6%	1.50	−0.8%
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For more results, including **price fairness**: https://arxiv.org/pdf/2308.01436

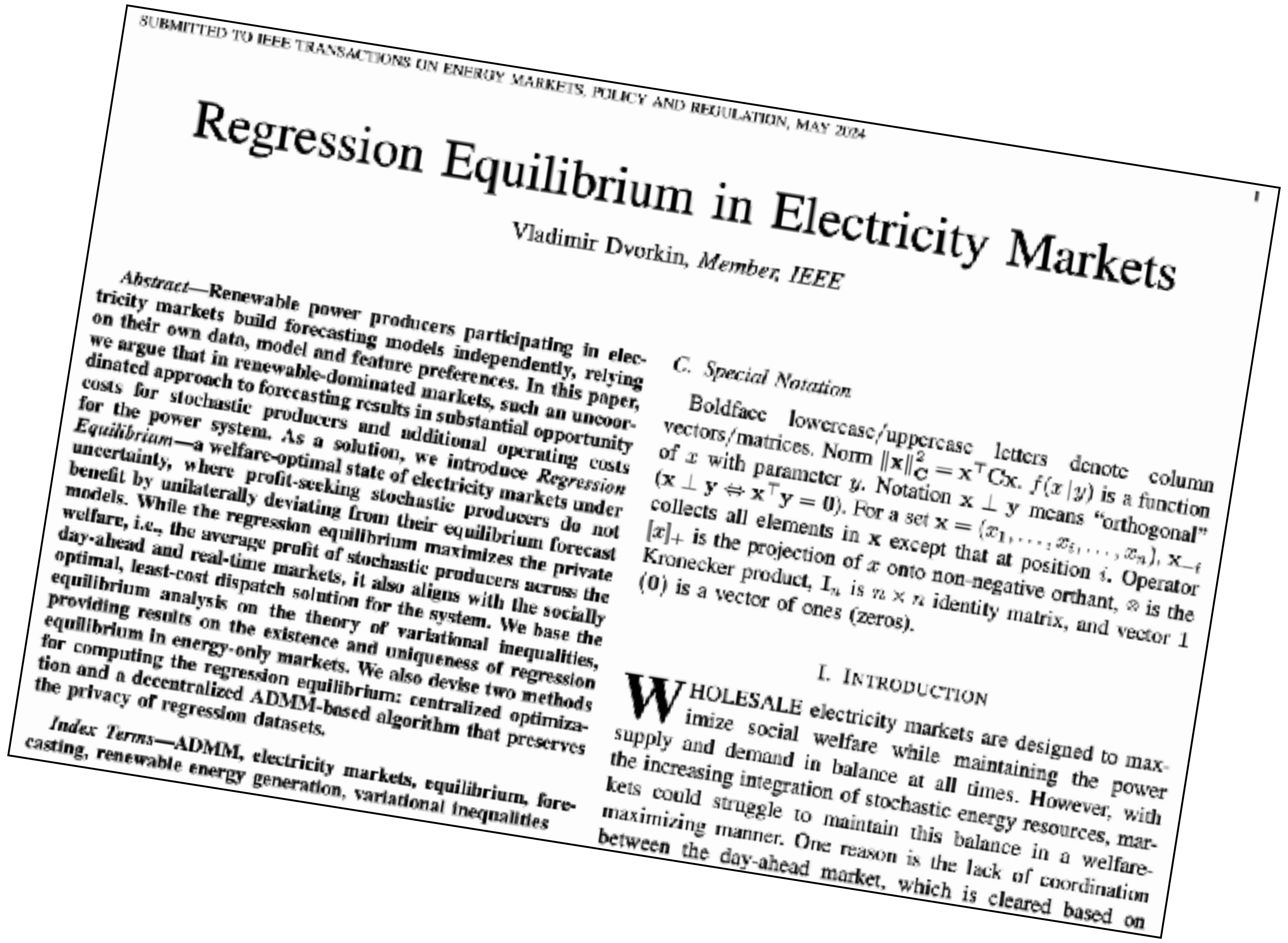
Agenda

Introduction

Controlling the impact of ML errors on electricity pricing

Nash equilibrium of ML models in electricity markets

Concluding remarks



SUBMITTED TO IEEE TRANSACTIONS ON ENERGY MARKETS, POLICY AND REGULATION, MAY 2024 1

Regression Equilibrium in Electricity Markets

Vladimir Dvorkin, *Member, IEEE*

***Abstract*—Renewable power producers participating in electricity markets build forecasting models independently, relying on their own data, model and feature preferences. In this paper, we argue that in renewable-dominated markets, such an uncoordinated approach to forecasting results in substantial opportunity costs for stochastic producers and additional operating costs for the power system. As a solution, we introduce *Regression Equilibrium*—a welfare-optimal state of electricity markets under uncertainty, where profit-seeking stochastic producers do not benefit by unilaterally deviating from their equilibrium forecast models. While the regression equilibrium maximizes the private welfare, i.e., the average profit of stochastic producers across the day-ahead and real-time markets, it also aligns with the socially optimal, least-cost dispatch solution for the system. We base the equilibrium analysis on the theory of variational inequalities, providing results on the existence and uniqueness of regression equilibrium in energy-only markets. We also devise two methods for computing the regression equilibrium: centralized optimization and a decentralized ADMM-based algorithm that preserves the privacy of regression datasets.**

***Index Terms*—ADMM, electricity markets, equilibrium, forecasting, renewable energy generation, variational inequalities**

C. Special Notation

Boldface lowercase/uppercase letters denote column vectors/matrices. Norm $\|\mathbf{x}\|^2_{\mathbf{C}} = \mathbf{x}^\top\mathbf{C}\mathbf{x}$. $f(x\,|\,y)$ is a function of x with parameter y. Notation $\mathbf{x} \perp \mathbf{y}$ means "orthogonal" ($\mathbf{x} \perp \mathbf{y} \Leftrightarrow \mathbf{x}^\top\mathbf{y} = 0$). For a set $\mathbf{x} = (x_1, \dots, x_i, \dots, x_n)$, $\mathbf{x}_{-i}$ collects all elements in $\mathbf{x}$ except that at position i. Operator $[x]_+$ is the projection of x onto non-negative orthant, $\otimes$ is the Kronecker product, $\mathbf{I}_n$ is $n \times n$ identity matrix, and vector $\mathbf{1}$ $(\mathbf{0})$ is a vector of ones (zeros).

I. INTRODUCTION

WHOLESALE electricity markets are designed to maximize social welfare while maintaining the power supply and demand in balance at all times. However, with the increasing integration of stochastic energy resources, markets could struggle to maintain this balance in a welfare-maximizing manner. One reason is the lack of coordination between the day-ahead market, which is cleared based on

Baseline approach to wind power forecasting:

- Collect a training dataset $\mathcal{D} = \{(\varphi_1, \mathbf{w}_1), \dots, \varphi_n, \mathbf{w}_n)\}$
- Machine learning model $\mathbb{W}_{\boldsymbol{\theta}} : \mathcal{F} \mapsto \mathcal{W}$ with parameter $\boldsymbol{\theta}$
- Learn optimal parameter $\boldsymbol{\theta}^\star$ by minimizing a prediction loss

$$\underset{\|\boldsymbol{\theta}\|_1 \leqslant \tau}{\text{min.}} \quad \mathcal{L}(\boldsymbol{\theta} \,|\, \mathcal{D}) = \frac{1}{n}\sum_{i=1}^{n} \|\mathbb{W}_{\boldsymbol{\theta}}(\varphi_i) - \mathbf{w}_i\|_2^2$$

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Revenue-optimal forecasting [PCK07, CK19, WSC23]:

1. Day-ahead stage: LMP $\boldsymbol{\lambda}_1$ pricing the forecast of wind power
2. Real-time stage: LMP $\boldsymbol{\lambda}_2$ pricing any forecast deviation

$$\underset{\|\theta\|_1 \leqslant \tau}{\text{max.}} \quad \mathcal{R}^{W}(\theta \,|\, \mathcal{D}, \boldsymbol{\lambda}_1, \boldsymbol{\lambda}_2) = \frac{1}{n}\sum_{i=1}^{n}\Big(\underbrace{\boldsymbol{\lambda}_{1i}\mathbb{W}_{\theta}(\varphi_i)}_{\text{day-ahead revenue}} + \underbrace{\boldsymbol{\lambda}_{2i}(\mathbf{w}_i - \mathbb{W}_{\theta}(\varphi_i))}_{\text{real-time revenue}}\Big)$$

Regression equilibrium in two-stage electricity markets [Dvo24]

Optimization of wind power producers

$$\underset{\|\boldsymbol{\theta}_j\| \leqslant \tau_j}{\text{max.}} \quad \mathcal{R}^W(\boldsymbol{\theta}_j | \mathcal{D}_j, \boldsymbol{\lambda}_1, \boldsymbol{\lambda}_2) - \gamma \cdot \mathcal{L}(\boldsymbol{\theta}_j | \mathcal{D}_j)$$

for all producers $j \in 1, \dots, b$

Regression equilibrium in two-stage electricity markets [Dvo24]

Optimization of wind power producers

$$\underset{\|\boldsymbol{\theta}_j\|\leqslant\tau_j}{\text{max.}} \quad \underbrace{\mathcal{R}^{W}(\boldsymbol{\theta}_j|\mathcal{D}_j,\boldsymbol{\lambda}_1,\boldsymbol{\lambda}_2)}_{\text{expected revenue}} - \underbrace{\gamma\cdot\mathcal{L}(\boldsymbol{\theta}_j|\mathcal{D}_j)}_{\text{regularization by prediction loss}}$$

for all producers $j \in 1,\ldots,b$

feature selection (constraint $\|\boldsymbol{\theta}_j\|\leqslant\tau_j$)

Optimization of wind power producers

$$\underset{\|\boldsymbol{\theta}_j\|\leqslant\tau_j}{\text{max.}} \quad \mathcal{R}^W(\boldsymbol{\theta}_j|\mathcal{D}_j,\boldsymbol{\lambda}_1,\boldsymbol{\lambda}_2) - \gamma\cdot\mathcal{L}(\boldsymbol{\theta}_j|\mathcal{D}_j)$$

for all producers $j\in 1,\dots,b$

Optimization of controllable generators

$$\underset{\mathbf{p}_i,\mathbf{r}_i\in\mathcal{G}}{\text{max.}} \quad \mathcal{R}^G(\mathbf{p}_i,\mathbf{r}_i \mid \boldsymbol{\lambda}_{1i},\boldsymbol{\lambda}_{2i}) - c\,(\mathbf{p}_i,\mathbf{r}_i)$$

for all training samples $i\in\mathcal{D}_{1:b}$

Regression equilibrium in two-stage electricity markets [Dvo24]

Optimization of wind power producers

$$\max_{\|\boldsymbol{\theta}_j\| \leqslant \tau_j} \quad \mathcal{R}^W(\boldsymbol{\theta}_j | \mathcal{D}_j, \boldsymbol{\lambda}_1, \boldsymbol{\lambda}_2) - \gamma \cdot \mathcal{L}(\boldsymbol{\theta}_j | \mathcal{D}_j)$$

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for all training samples $i \in \mathcal{D}_{1:b}$

revenue from generation and regulation

generation and regulation cost

Regression equilibrium in two-stage electricity markets [Dvo24]

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Others

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for all training samples $i \in \mathcal{D}_{1:b}$

Others

Market-clearing conditions at the 1st and 2nd stages

$$\mathbf{0} \leqslant \boldsymbol{\lambda}_{1i} \perp \mathbf{p}_i + \sum_{j=1}^{b} \mathbb{W}_{\theta_j}(\varphi_i) - \mathbf{d} \geqslant \mathbf{0}, \quad \mathbf{0} \leqslant \boldsymbol{\lambda}_{2i} \perp \mathbf{r}_i + \sum_{j=1}^{b} \mathbf{w}_{ji} - \sum_{j=1}^{b} \mathbb{W}_{\theta_j}(\varphi_i) \geqslant \mathbf{0}$$

for all training samples $i \in \mathcal{D}_{1:b}$

Optimization of wind power producers

$$\max_{\|\boldsymbol{\theta}_j\| \leqslant \tau_j} \quad \mathcal{R}^W(\boldsymbol{\theta}_j|\mathcal{D}_j, \boldsymbol{\lambda}_1, \boldsymbol{\lambda}_2) - \gamma \cdot \mathcal{L}(\boldsymbol{\theta}_j|\mathcal{D}_j)$$

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Optimization of controllable generators

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Others

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for all training samples $i \in \mathcal{D}_{1:b}$

Assumptions:

- Class of ML models $\mathbb{W}_{\boldsymbol{\theta}}$ is **convex** in $\boldsymbol{\theta}$, e.g., kernel regression
- Training datasets are such that $n \gg \text{card}[\boldsymbol{\varphi}]$ (unique regression solution)
- The intersection of private feasible regions is compact (at least one feasible dispatch $\forall i \in \mathcal{D}_{1:b}$)

Main result: regression equilibrium exists and is unique!

Optimization of wind power producers

$$\max_{\|\boldsymbol{\theta}_j\| \leqslant \tau_j} \quad \mathcal{R}^W(\boldsymbol{\theta}_j|\mathcal{D}_j, \boldsymbol{\lambda}_1, \boldsymbol{\lambda}_2) - \gamma \cdot \mathcal{L}(\boldsymbol{\theta}_j|\mathcal{D}_j)$$

for all producers $j \in 1, \ldots, b$

Optimization of controllable generators

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Others

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for all training samples $i \in \mathcal{D}_{1:b}$

Equilibrium regression profile $\boldsymbol{\Theta}^\star = (\boldsymbol{\theta}_1^\star, \ldots, \boldsymbol{\theta}_b^\star)$**, such that:**

- Feasible operation of the power gird and markets
- Maximized wind power profits, with no incentives to deviate
- Minimized expected dispatch costs across the two markets

Regression equilibrium in two-stage electricity markets [Dvo24]

Optimization of wind power producers

$$\max_{\|\boldsymbol{\theta}_j\| \leqslant \tau_j} \quad \mathcal{R}^W(\boldsymbol{\theta}_j | \mathcal{D}_j, \boldsymbol{\lambda}_1, \boldsymbol{\lambda}_2) - \gamma \cdot \mathcal{L}(\boldsymbol{\theta}_j | \mathcal{D}_j)$$

for all producers $j \in 1, \dots, b$

Optimization of controllable generators

$$\max_{\mathbf{p}_i, \mathbf{r}_i \in \mathcal{G}} \quad \mathcal{R}^G(\mathbf{p}_i, \mathbf{r}_i \mid \boldsymbol{\lambda}_{1i}, \boldsymbol{\lambda}_{2i}) - c(\mathbf{p}_i, \mathbf{r}_i)$$

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Equilibrium regression profile $\Theta^\star = (\theta_1^\star, \dots, \theta_b^\star)$, such that:

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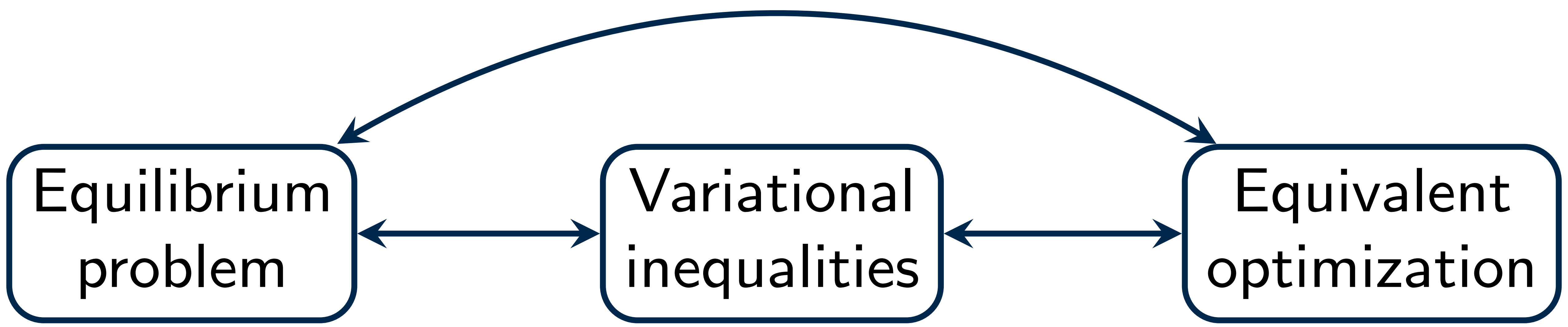
How to compute equilibrium regression $\Theta^\star$?



- Equilibrium problem: stacks many private optimization problems
- Variational inequalities (VI): analyzes the interaction between private optimization problems
- In some special cases (like ours), VI connects equilibrium to a centralized optimization

For more details visit Appenix A in: https://arxiv.org/pdf/2405.17753

Computing regression equilibrium: centralized optimization

- By the Symmetry Principle Theorem [FP03], there exists an equivalent opt solving the equilibrium
- ... which happens to minimizes the expected generation and regulation costs
- ... thus enhancing the temporal coordination of day-ahead and real-time markets

Day-ahead + real-time cost

$$
\begin{aligned}
\min_{\boldsymbol{\Theta},\mathbf{p},\mathbf{r}} \quad & \frac{1}{n}\sum_{i=1}^{n} c\left(\mathbf{p}_i, \mathbf{r}_i\right) + \gamma \left\|\boldsymbol{\Theta}\varphi_i - \mathbf{w}_i\right\|_2^2 && \text{regularized expected cost} \\
\text{s.to} \quad & \mathbf{1}^\top(\mathbf{p}_i + \boldsymbol{\Theta}\varphi_i - \mathbf{d}) = 0, && \text{day-ahead power balance} \\
& \mathbf{1}^\top(\mathbf{r}_i - \boldsymbol{\Theta}\varphi_i + \mathbf{w}_i) = 0, && \text{real-time power balance} \\
& |\mathbf{F}(\mathbf{p}_i + \boldsymbol{\Theta}\varphi_i - \mathbf{d})| \leqslant \overline{\mathbf{f}}, && \text{day-ahead power flow limit} \\
& |\mathbf{F}(\mathbf{p}_i + \boldsymbol{\Theta}\varphi_i - \mathbf{d}) \\
& \quad + \mathbf{F}(\mathbf{r}_i - \boldsymbol{\Theta}\varphi_i + \mathbf{w}_i)| \leqslant \overline{\mathbf{f}}, && \text{real-time power flow limit} \\
& \underline{\mathbf{p}} \leqslant \mathbf{p}_i + \mathbf{r}_i \leqslant \overline{\mathbf{p}}, && \text{generation limit} \\
& |\mathbf{r}_i| \leqslant \overline{\mathbf{r}}, \quad \forall i = 1, \dots, n, && \text{regulation limit} \\
& |\boldsymbol{\Theta}| \leqslant \tau && \text{equilibrium feature selection}
\end{aligned}
$$

- For more details visit Appenix A in: https://arxiv.org/pdf/2405.17753

Computing regression equilibrium: Walrasian auction and ADMM

Step 1 Primal update of each wind power producer:

$$\boldsymbol{\theta}^k \leftarrow \max_{\|\boldsymbol{\theta}\|\leqslant\tau} \quad \mathcal{R}^W(\boldsymbol{\theta}|\mathcal{D}, \boldsymbol{\lambda}_1^k, \boldsymbol{\lambda}_2^k) - \gamma \cdot \mathcal{L}(\boldsymbol{\theta}|\mathcal{D})$$

Step 2 Primal update of each conventional generator:

$$\mathbf{p}^k, \mathbf{r}^k \leftarrow \max_{\mathbf{p},\mathbf{r}\in\mathcal{G}} \quad \mathcal{R}^G(\mathbf{p}, \mathbf{r} \mid \boldsymbol{\lambda}_1^k, \boldsymbol{\lambda}_2^k) - c\,(\mathbf{p}, \mathbf{r})$$

Step 3 Electricity price updates:

$$\boldsymbol{\lambda}_1^{k+1} \leftarrow \left[\boldsymbol{\lambda}_1^k - \varrho\left(\mathbf{p}^k + \mathbb{W}_{\boldsymbol{\theta}^k}(\varphi) - \mathbf{d}\right)\right]_+$$
$$\boldsymbol{\lambda}_2^{k+1} \leftarrow \left[\boldsymbol{\lambda}_2^k - \varrho\left(\mathbf{r}^k + \mathbf{w} - \mathbb{W}_{\boldsymbol{\theta}^k}(\varphi)\right)\right]_+$$

- Resembles Walrasian auction: Equilibrium is computed via price exchange
- Proprietary training datasets are localized and not exchanged

Computing regression equilibrium: Walrasian auction and ADMM

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$$\boldsymbol{\theta}^k \leftarrow \max_{\|\boldsymbol{\theta}\| \leqslant \tau} \; \mathcal{R}^W(\boldsymbol{\theta}|\mathcal{D}, \boldsymbol{\lambda}_1^k, \boldsymbol{\lambda}_2^k) - \gamma \cdot \mathcal{L}(\boldsymbol{\theta}|\mathcal{D}) \underbrace{+ \frac{\varrho}{2}\left\|\mathbf{p}^{k-1} + \mathbb{W}_{\boldsymbol{\theta}}(\varphi) - \mathbf{d}\right\|_2^2 + \frac{\varrho}{2}\left\|\mathbf{r}^{k-1} + \mathbf{w} - \mathbb{W}_{\boldsymbol{\theta}}(\varphi)\right\|_2^2}_{\text{ADMM feasibility terms}}$$

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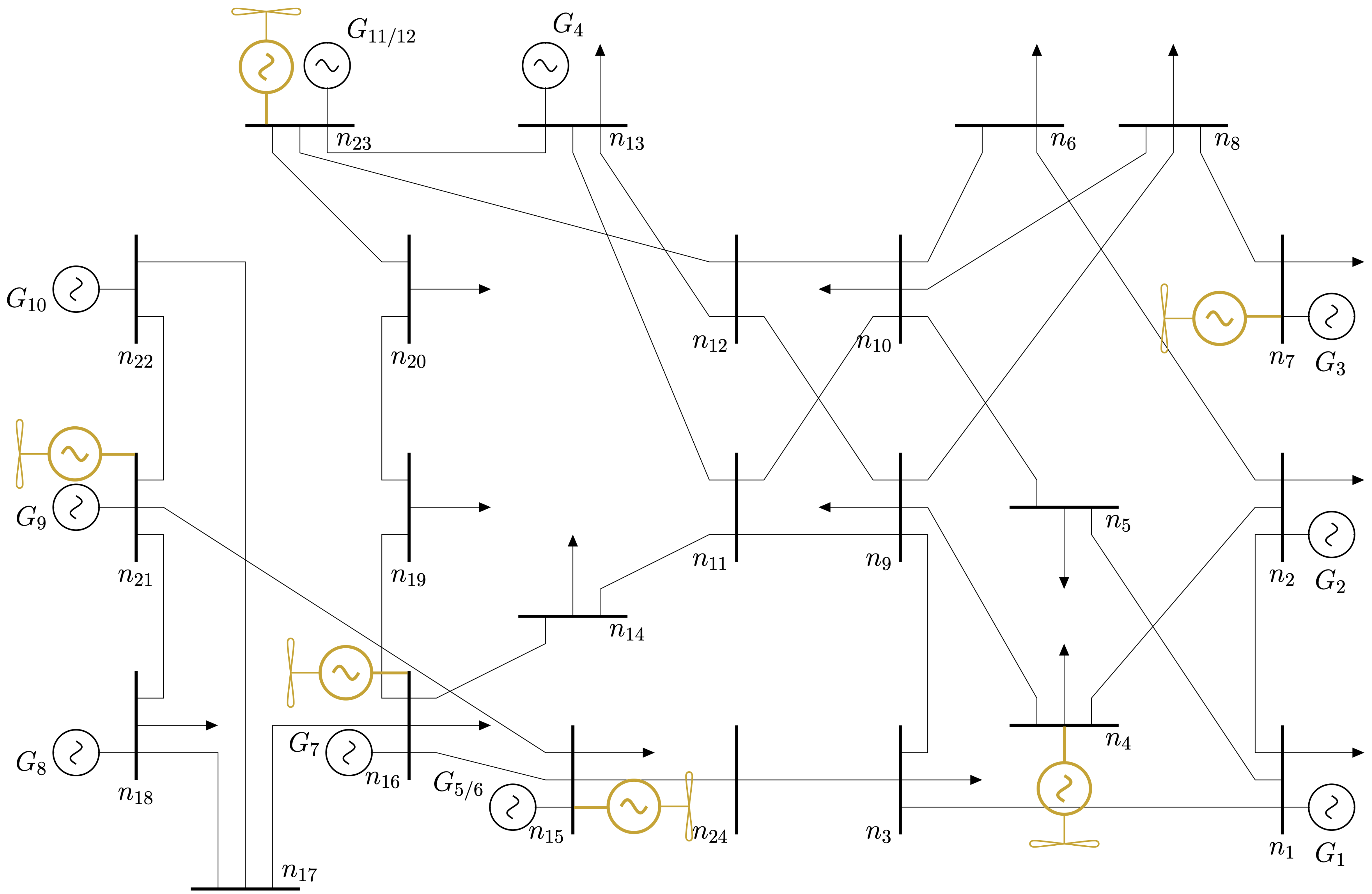
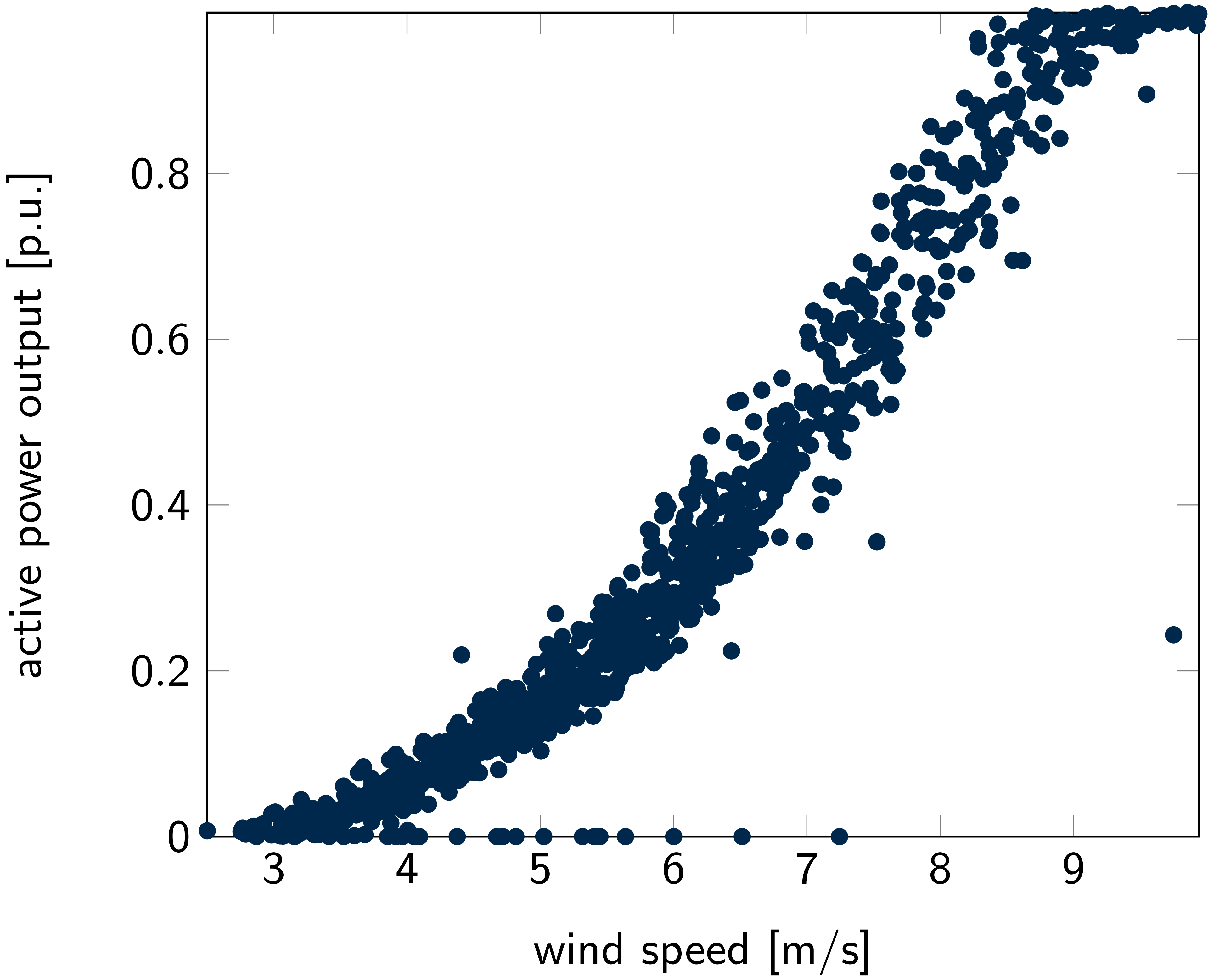
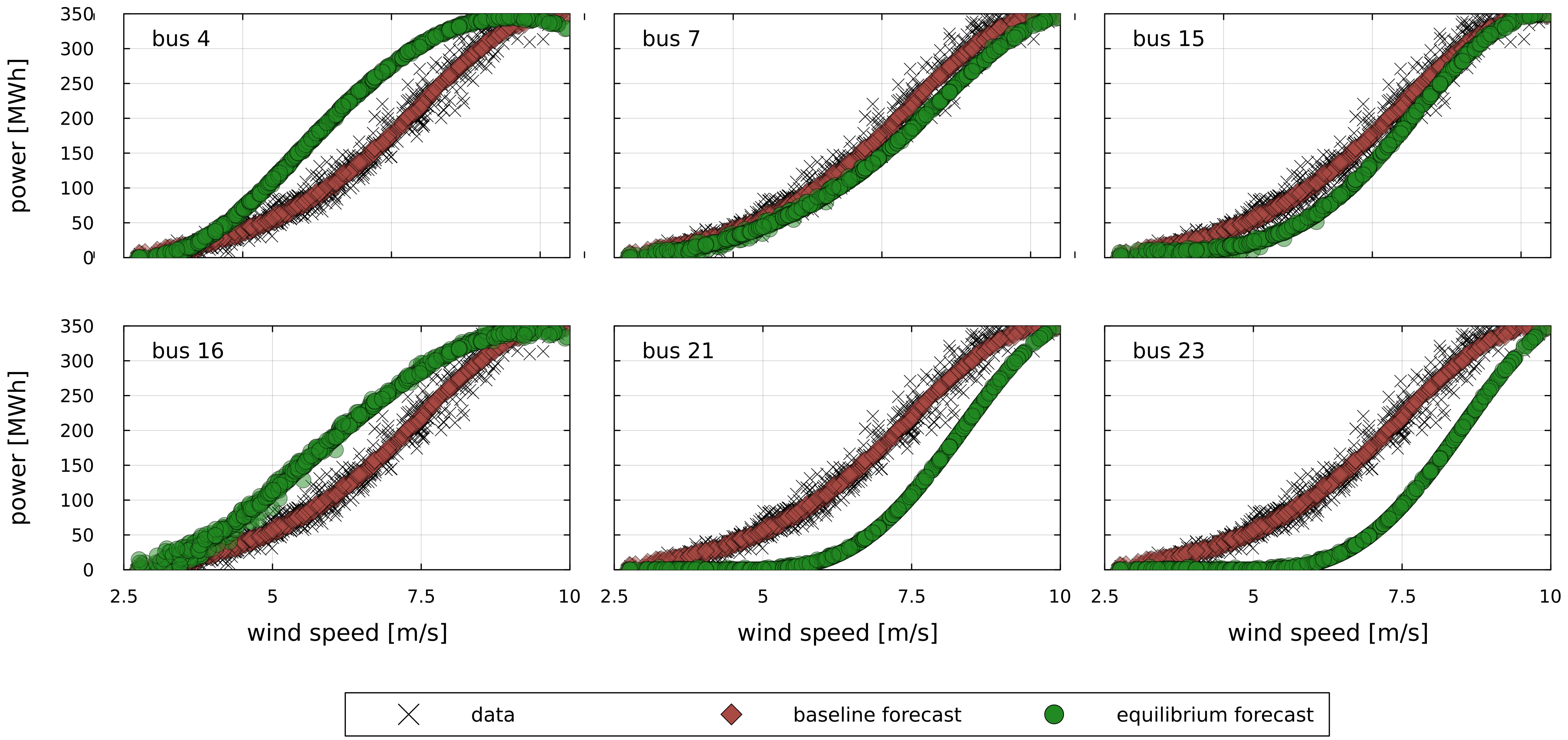




- 6 with farms with identical data and features
- Cover 38.4% of load at peak generation
- Kernel regression with 30 transformed features
- 5,000 training and 10,000 testing samples

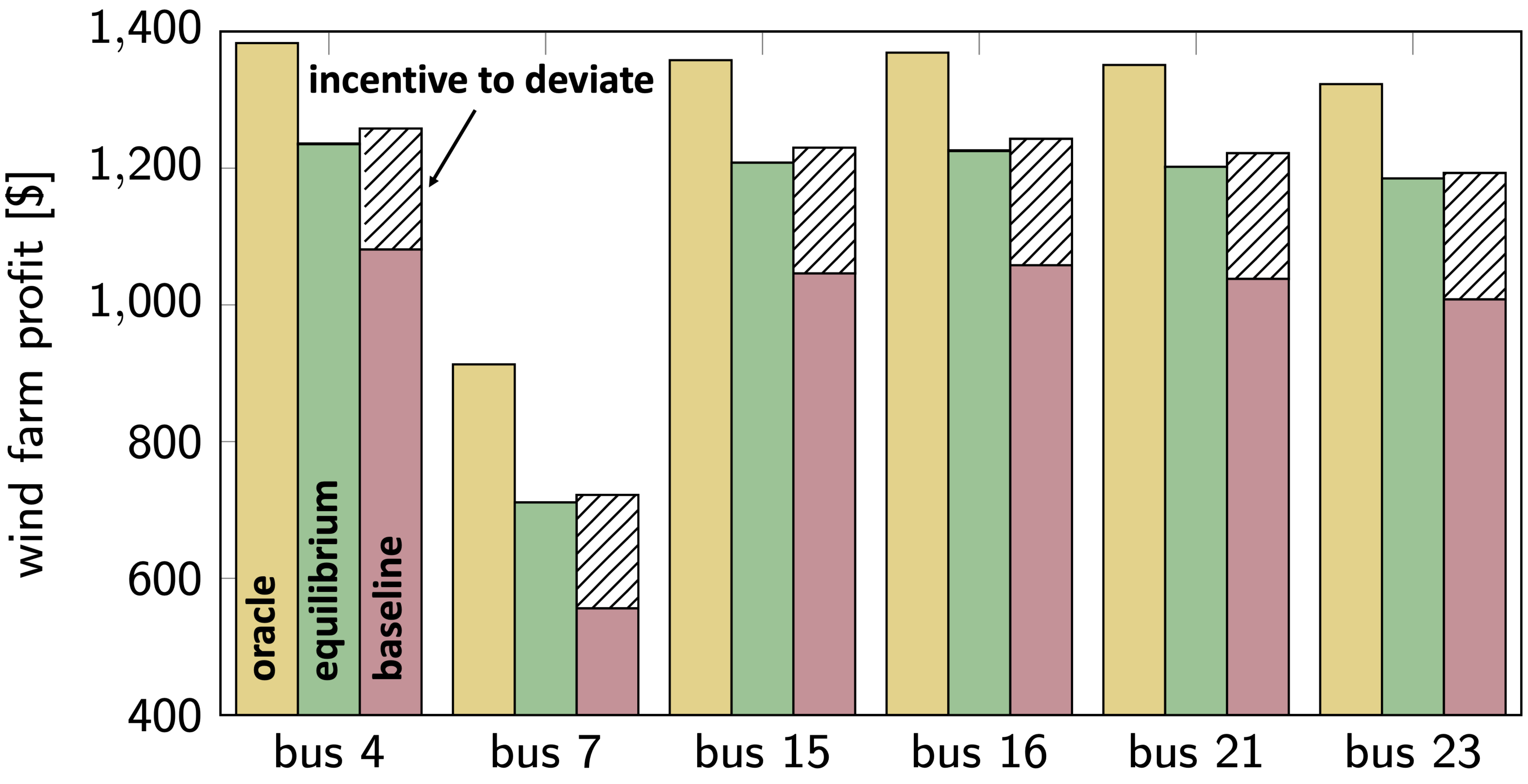
- Although data is the same, how do equilibrium forecasts depend on the wind farm location in the grid?
- What are the equilibrium benefits in terms profits (any incentives to deviate?) and cost of electricity?



- **Baseline:** minimizes a prediction error
- **Equilibrium:** maximizes wind farm profits

Systematic over- or under-prediction depending on the wind farm's location in the grid

Wind farm profits and incentives to deviate



- Equilibrium regression yields larger profits for all wind farms
- There are large profit incentives to unilaterally deviate from the baseline regression
- And (almost) no incentives to deviate from the equilibrium regression

Regression	RMSE, MWh	Average dispatch cost, $			Total dispatch cost error, $	
		total	day-ahead	real-time	average	$\text{CVaR}_{10\%}$
Oracle	——	$37,246$	$37,246$	——	——	——
Baseline	88	$39,223$	$37,459$	$1,764$	$1,977$	$8,626$
Equilibrium	395	$38,326$	$38,154$	172	$1,080$	$3,555$

- Baseline regression: minimal forecast error, yet results in large real-time cost
- Equilibrium regression: large forecast errors, withholds cheap generation from the day-ahead market; yet, results in very cheap real-time re-dispatch
- Saving of 2.4% on average, and 13.6% on average across 10% of the worst-case scenarios

Impact of regression equilibrium on dispatch costs

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- Baseline regression: minimal forecast error, yet results in large real-time cost
- Equilibrium regression: large forecast errors, withholds cheap generation from the day-ahead market; yet, results in very cheap real-time re-dispatch
- Saving of 2.4% on average, and 13.6% on average across 10% of the worst-case scenarios

Agenda

Concluding remarks

Part I:

- Erroneous ML models have a significant impact on pricing and dispatch decisions in electricity markets
- We integrate market-clearing optimization into training to inform them on specific decision objective

Part II:

- Network coupling of private ML models (ripple effect on the entire electricity market)
- Nash regression equilibrium syncs private models and yields maximum profits
- It implicitly minimizes the cost across day-ahead and real-time markets ...
- ...thus delivering some benefits of stochastic market design in the existing deterministic markets

Part 1

Thank you for your attention!

Part 2

ECE 598: Computational Power Systems

Term: Winter 2025
Credit Hours: 3 credits
Time: Fridays 10:30-13:30
Format : Lecture (75 min) + Break + Tutorial (75 min)
Instructor: Vladimir (Vlad) Dvorkin
E-mail: `dvorkin@umich.edu`

Course Description

The growing digitization of power systems and the rapid integration of renewable energy resources call for new computational algorithms to support power system operations and electricity markets. In this course, students will learn the core computational problems in power systems and modern algorithms to solve those problems, while managing the trade-offs between performance, speed and data requirements.

In the first part of the course, students will familiarize themselves with optimization problems in power systems, including economic dispatch and market clearing for transmission grids, as well as voltage control and peer-to-peer markets for distribution grids. They will also learn how machine learning (ML) aids in solving these optimization problems. In the second part, the focus will be on decentralized/distributed decision-making in high-voltage and distribution grids, and how agents can autonomously solve dispatch, control, and learning problems using decentralized/distributed algorithms, such as dual decomposition, ADMM, and their variants. In the third part, students will acquire prescriptive analytics skills: it will introduce algorithms for decision-focused learning in the context of renewable power forecasting and other relevant analytical tasks. Students will work on final projects (to be agreed upon with the instructor) and present the results to their peers. Possible project topics include:

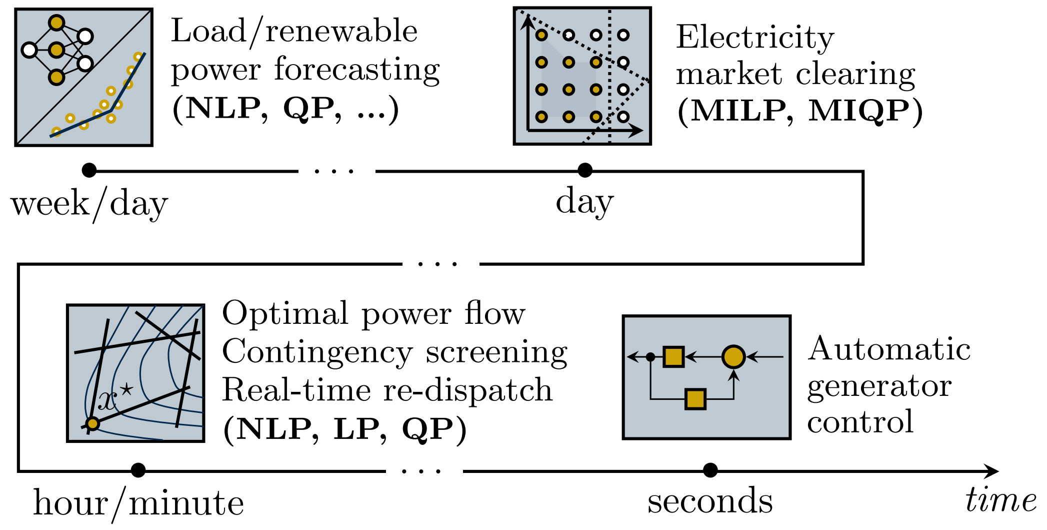

Figure 1: Computational power systems timeline

- Decentralized electricity market designs
- Carbon-constrained electric power dispatch and pricing
- Optimization algorithms for voltage control in distribution grids
- Power grid coordination with adjacent infrastructures (e.g., with data centers)

Each weekly session will consist of a lecture and a follow-up tutorial on the lecture materials.

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