AI for Power Systems

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Georgia Institute of Technology

The AI4OPT Institute

AI Institute for Advances in Optimization

Use-Inspired Research

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Industrial Partners

Research

Education and Diversity

AI Institute for Advances in Optimization

Seth Bonder

International

Innovation

The Beauty of Optimization

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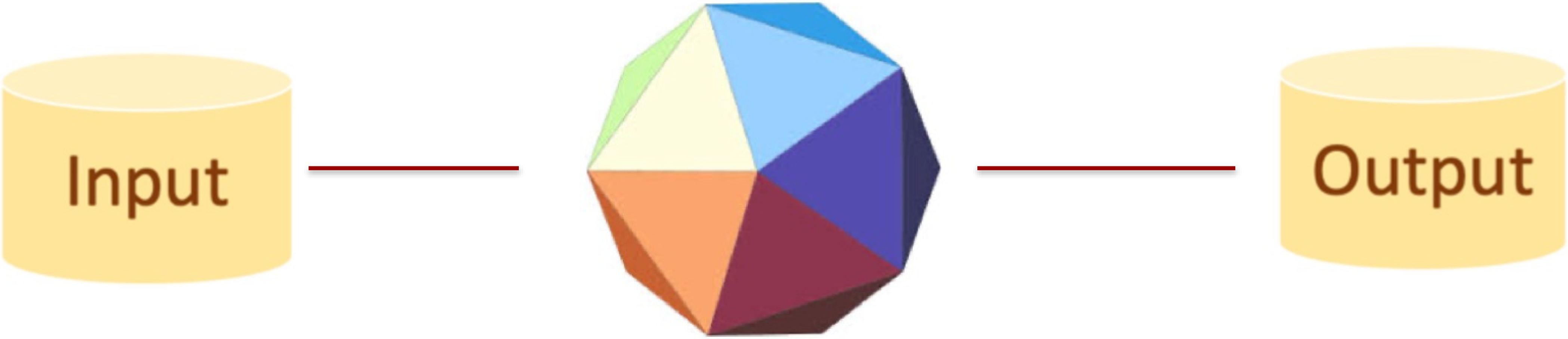
Optimization Model



Optimization Solver

The Challenges of Optimization

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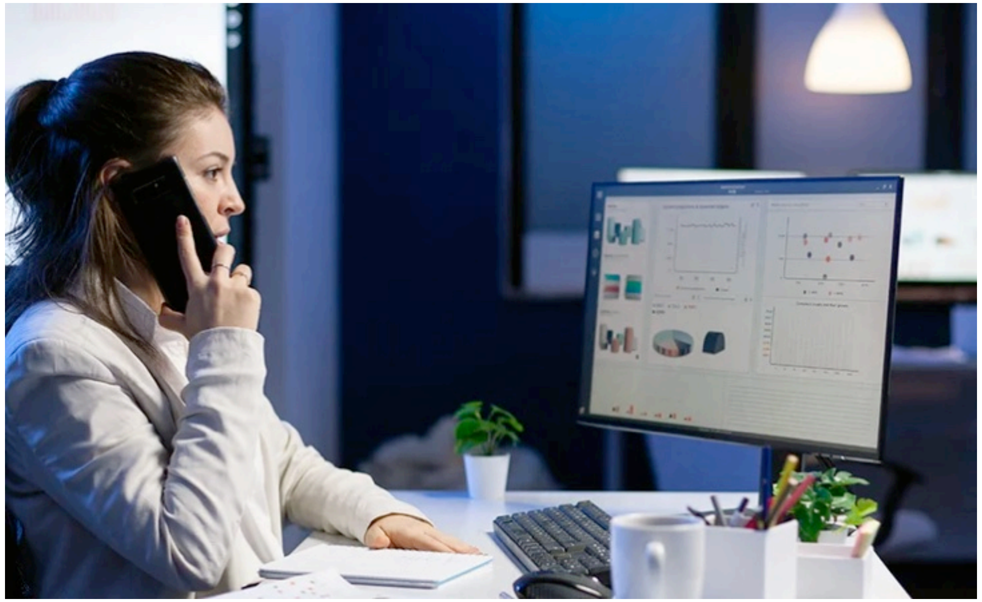
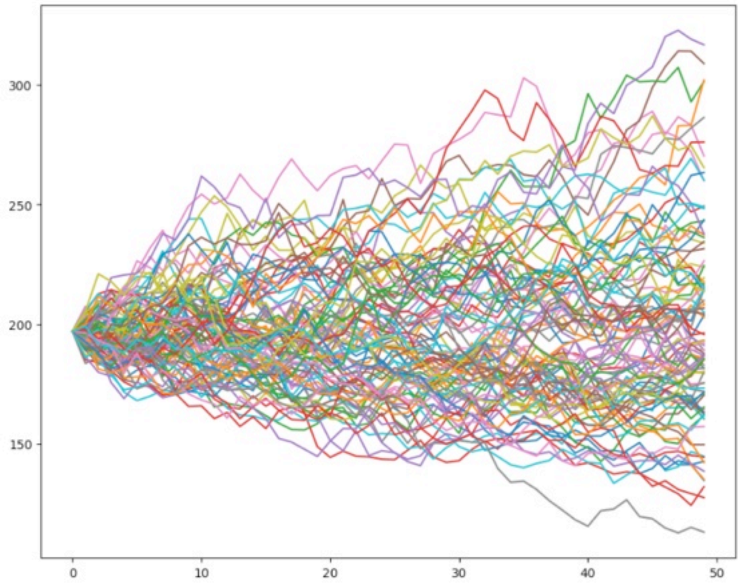
- Optimization may be too slow in some circumstances





Realities in the Fields

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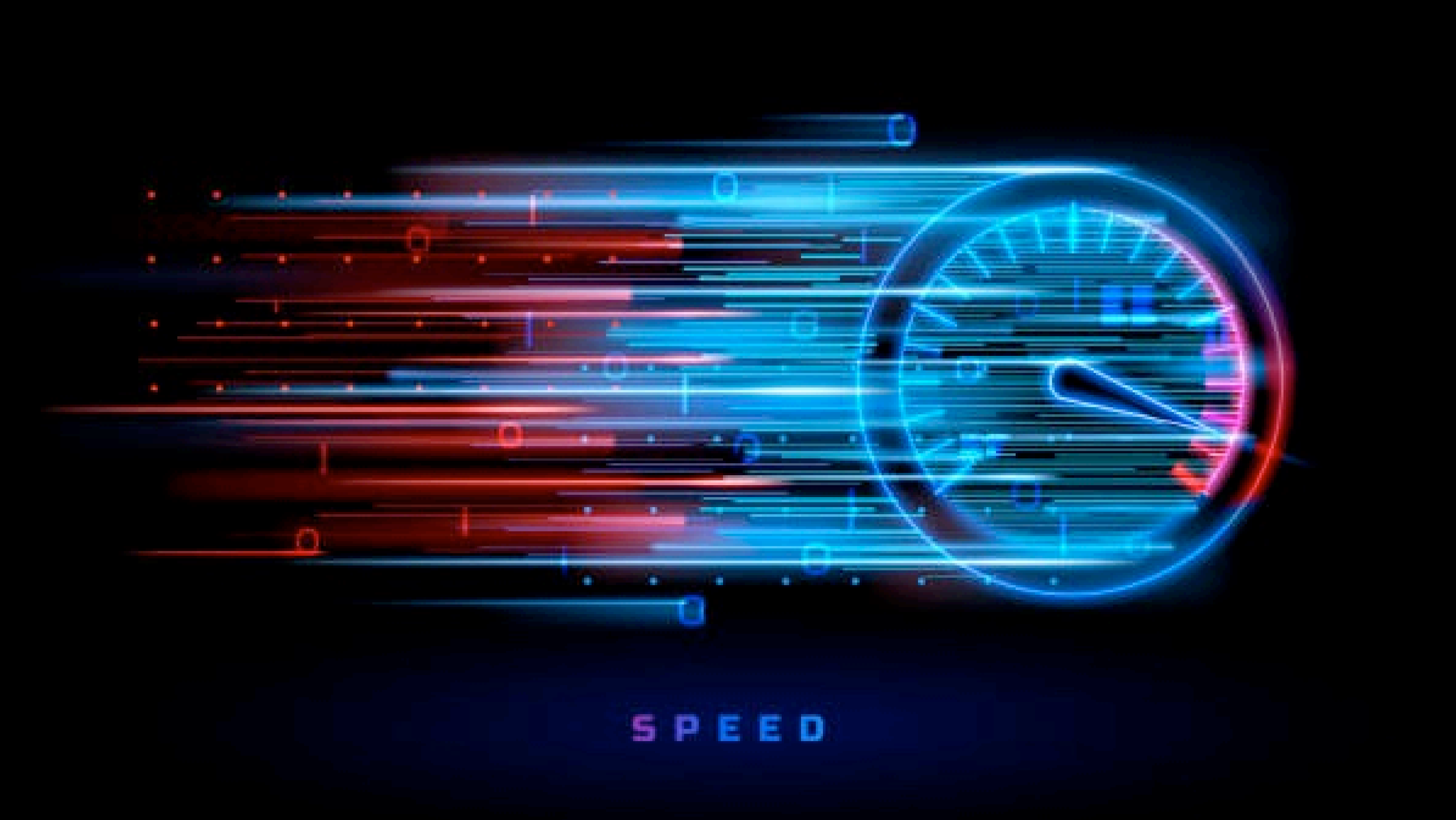
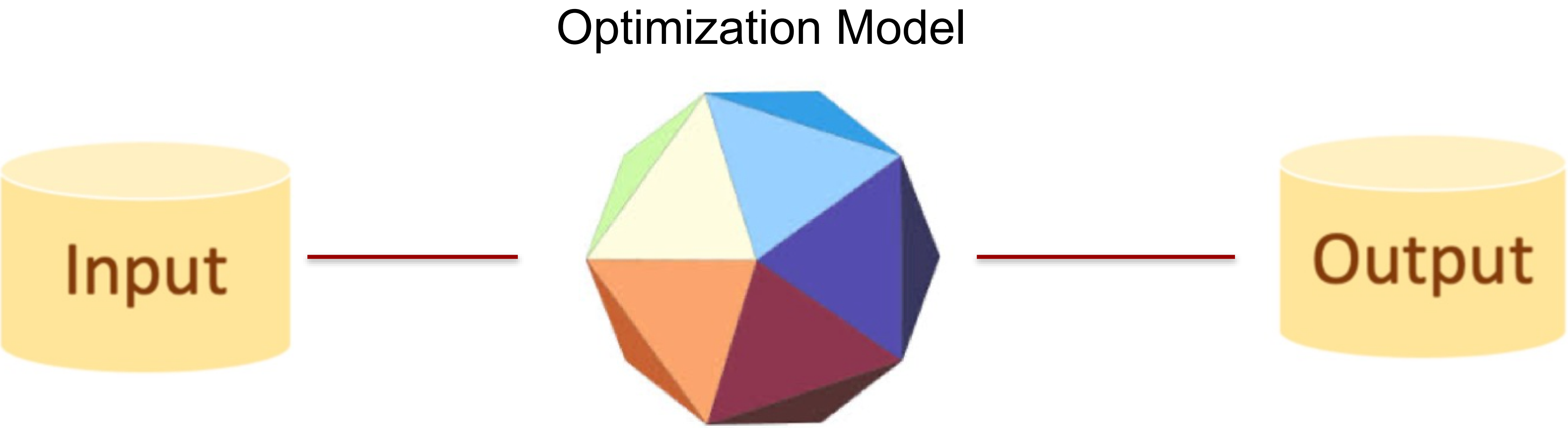
- Optimization over physical infrastructures

- Solving the same core problem repeatedly
  - in situations that are relatively stable
  - in situations where a lot of historical and forecasted data is available


SPEED

Optimization as a Function



$$\mathcal{O} : I^n \mapsto O^m$$

Parametric Machine Learning

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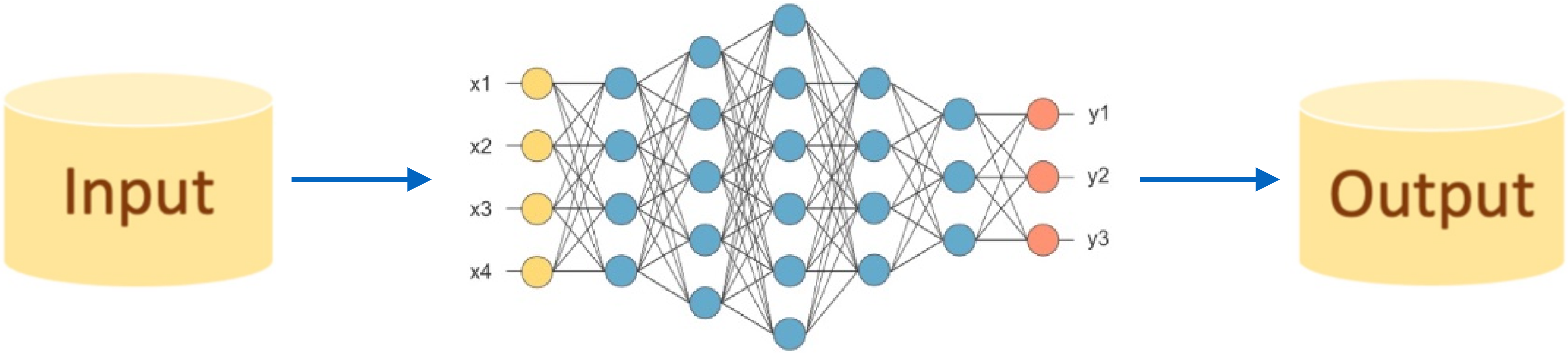
Machine Learning Model



$$\mathcal{M}_\theta : I^n \mapsto O^m$$

The Overall Approach

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- Considering a multi-parametric optimization
  – using a distribution of inputs
- Move the computational burden offline
  – through machine learning
- Learning offline
  – empirical risk minimization
- Evaluation at inference time / real time
  – on a specific input with orders of magnitude improvement in efficiency

$$\mathcal{M}_{\theta^*}(\mathbf{x})$$

Does it work?

The Challenges for AI in Engineering

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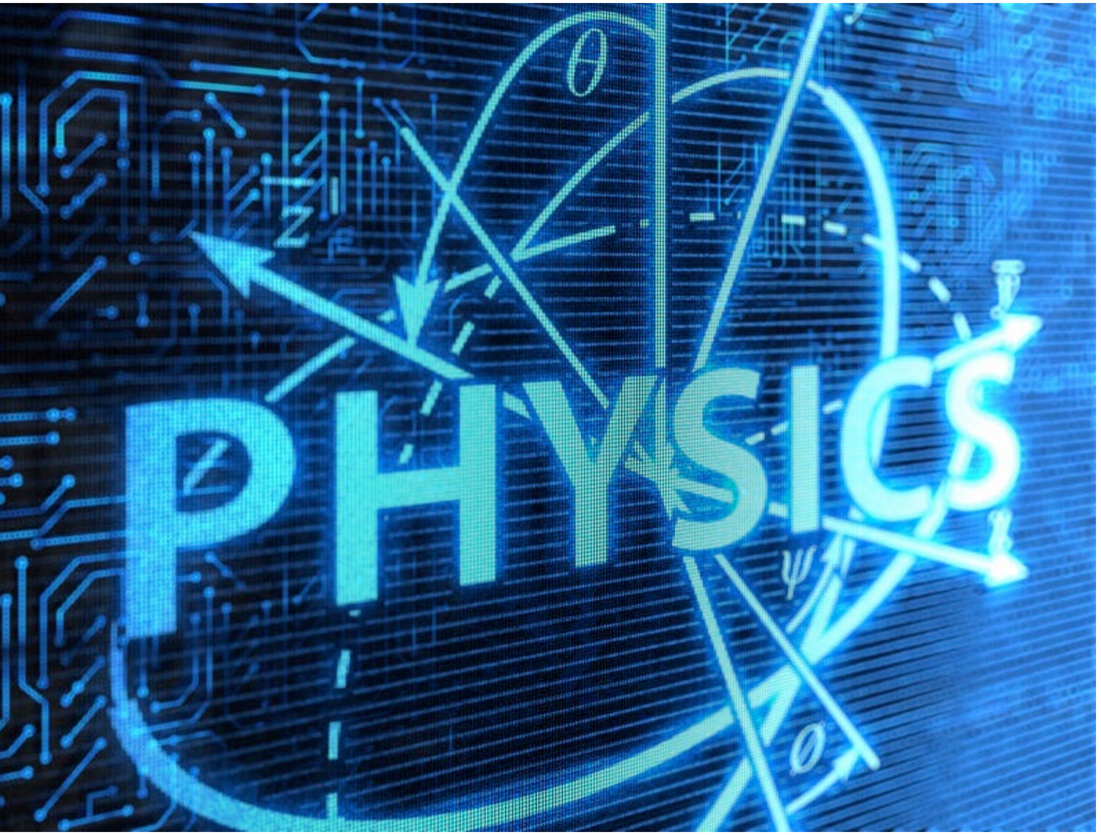
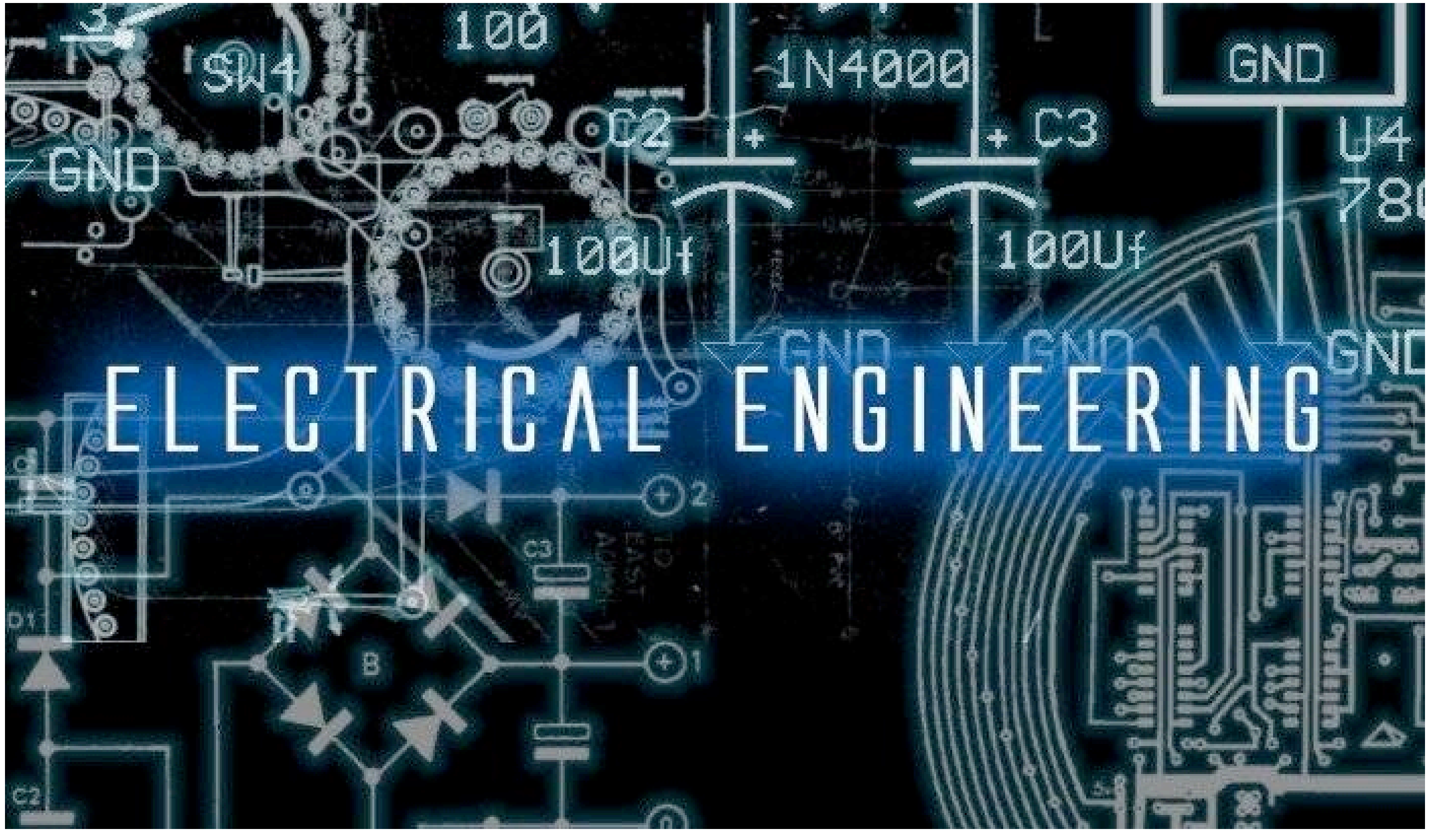
- Empirical risk minimization under constraints
  - physical, engineering, and/or business constraints
- Trustworthy AI by design
  - not as an after-thought
- Reliability
  - models to be deployed in critical infrastructures
- Performance guarantees
  - quality of solutions (e.g., optimality gaps)
- Scalability (and energy efficient)
  - input size of 1,000,000 and output size of 100,000

AI is Ready
for Critical Power Systems Applications

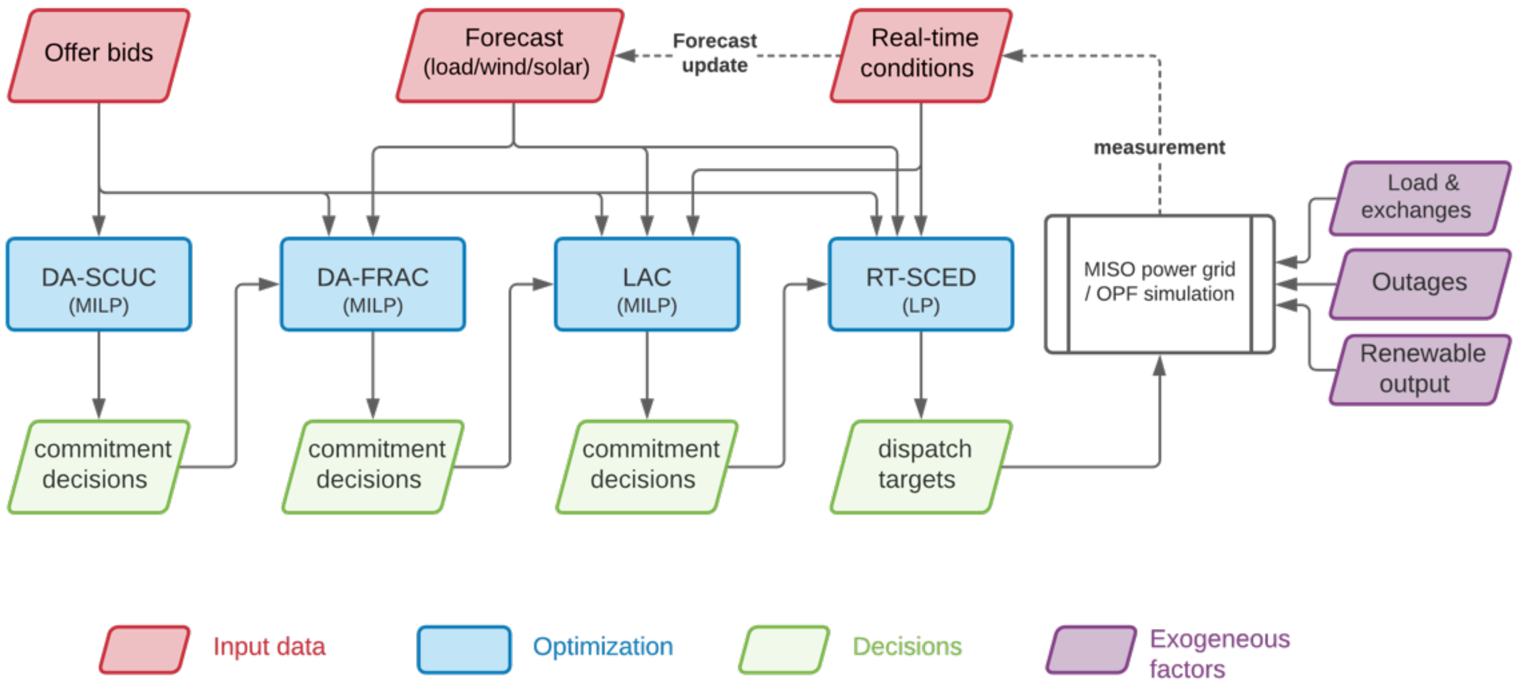
AI is the Key Technology Enabler for Critical Power Systems Applications


PHYSICS


ELECTRICAL ENGINEERING
GND
SW4
100
1N4000
C2
C3
100Uf
100Uf
GND
U4

Energy Systems Operator Pipeline

- A sequence of optimization problems to decide
  - **Commitments**: Which generators do we switch on/off?
  - **Dispatches**: How much power each generator produces and how much reserves it provides?



Keeping the lights on!

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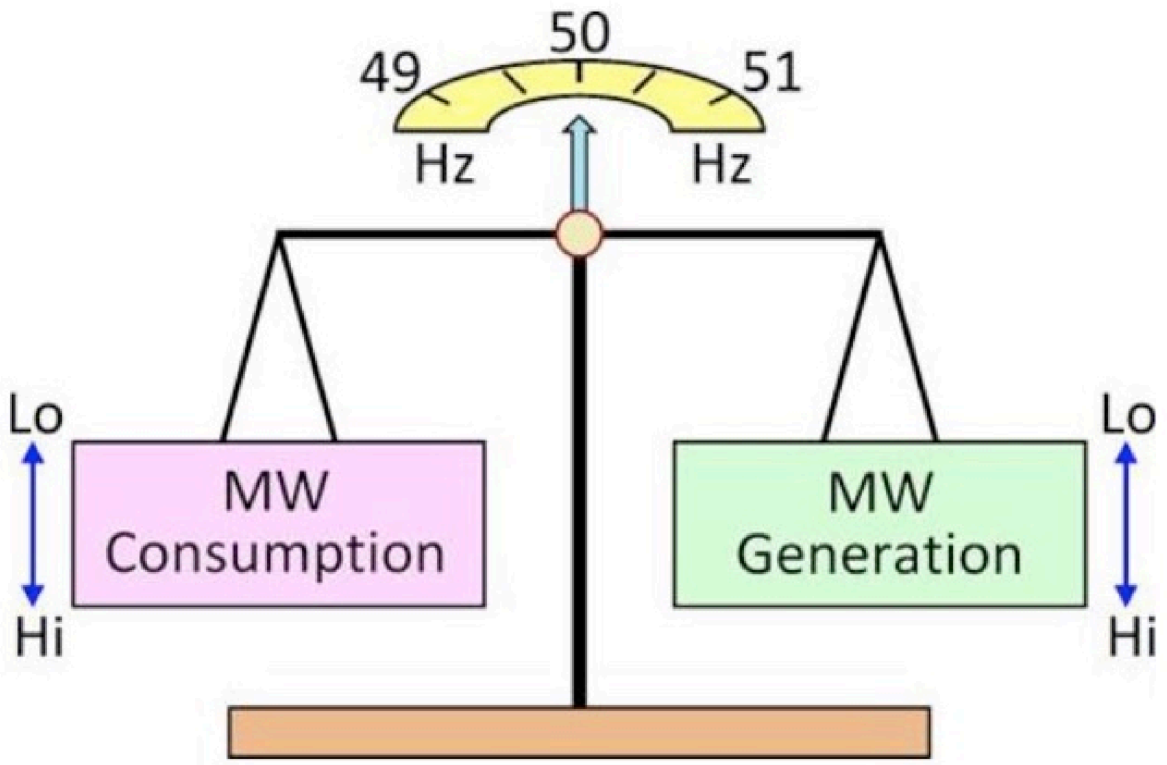
THE POWER BALANCE



Economic Dispatch with Reserves

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$$
\begin{aligned}
\min_{\mathbf{p},\mathbf{r},\xi} \quad & c(\mathbf{p}) + M\|\xi\|_1 \\
\text{s.t.} \quad & \mathbf{e}^\top \mathbf{p} = L, \\
& \mathbf{e}^\top \mathbf{r} \geq R, \\
& \mathbf{p} + \mathbf{r} \leq \bar{\mathbf{p}}, \\
& \mathbf{0} \leq \mathbf{p} \leq \bar{\mathbf{p}}, \\
& \mathbf{0} \leq \mathbf{r} \leq \bar{\mathbf{r}}, \\
& \underline{\mathbf{f}} - \xi \leq \Phi\mathbf{p} \leq \bar{\mathbf{f}} + \xi, \\
& \xi \geq \mathbf{0}.
\end{aligned}
$$

load = generation

Economic Dispatch with Reserves

AI Institute for Advances in Optimization

$$
\begin{aligned}
\min_{\mathbf{p},\mathbf{r},\xi} \quad & c(\mathbf{p}) + M\|\xi\|_1 \\
\text{s.t.} \quad & \mathbf{e}^\top \mathbf{p} = L, \\
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& \mathbf{0} \leq \mathbf{r} \leq \bar{\mathbf{r}}, \\
& \underline{\mathbf{f}} - \xi \leq \Phi\mathbf{p} \leq \bar{\mathbf{f}} + \xi, \\
& \xi \geq \mathbf{0}.
\end{aligned}
$$

enough reserves

Economic Dispatch with Reserves

AI Institute for Advances in Optimization

$$
\begin{aligned}
\min_{\mathbf{p},\mathbf{r},\xi} \quad & c(\mathbf{p}) + M\|\xi\|_1 \\
\text{s.t.} \quad & \mathbf{e}^\top \mathbf{p} = L, \\
& \mathbf{e}^\top \mathbf{r} \geq R, \\
& \mathbf{p} + \mathbf{r} \leq \bar{\mathbf{p}}, \\
& \mathbf{0} \leq \mathbf{p} \leq \bar{\mathbf{p}}, \\
& \mathbf{0} \leq \mathbf{r} \leq \bar{\mathbf{r}}, \\
& \underline{\mathbf{f}} - \xi \leq \Phi \mathbf{p} \leq \bar{\mathbf{f}} + \xi, \\
& \xi \geq \mathbf{0}.
\end{aligned}
$$

engineering constraints

Security-Constrained Economic Dispatch

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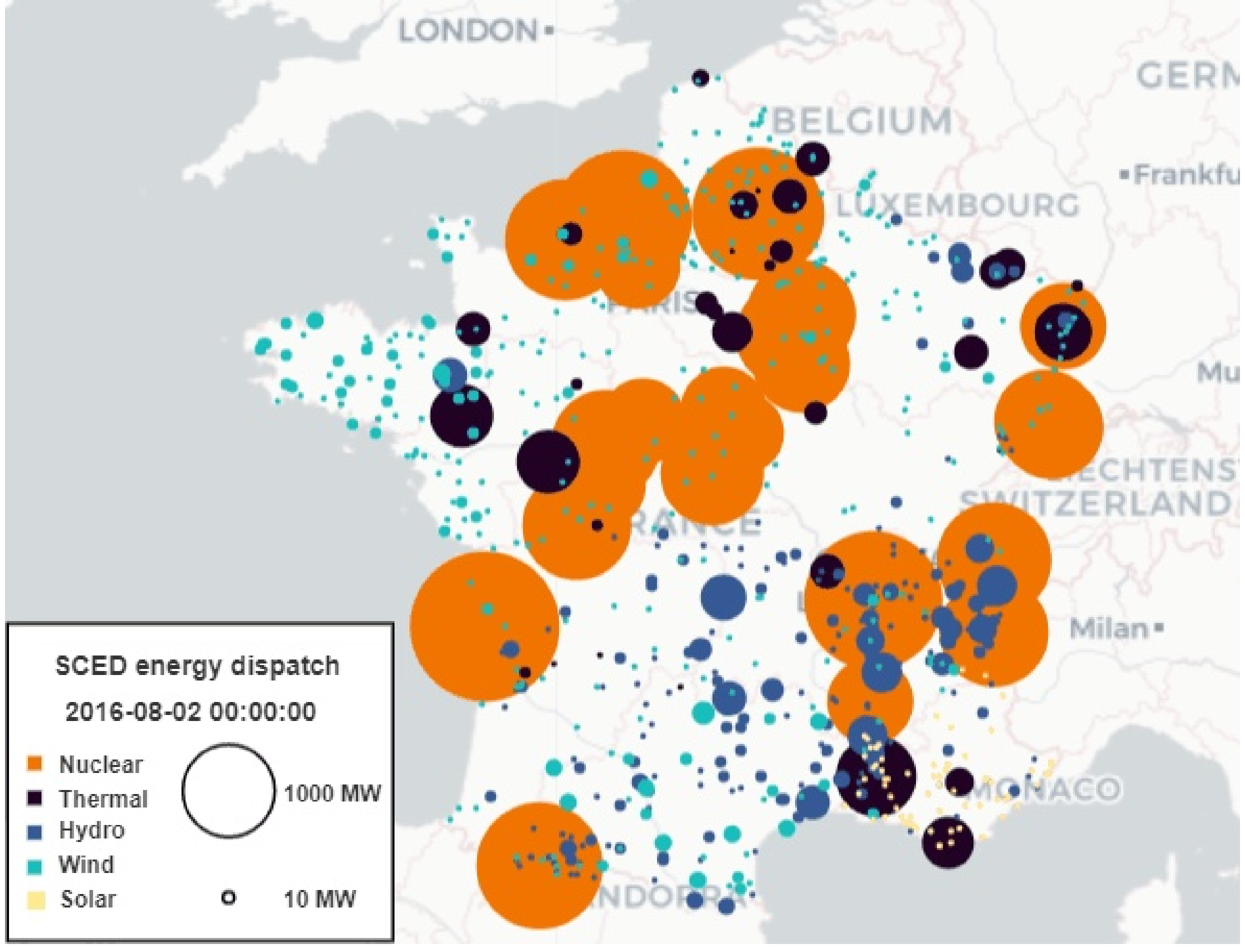

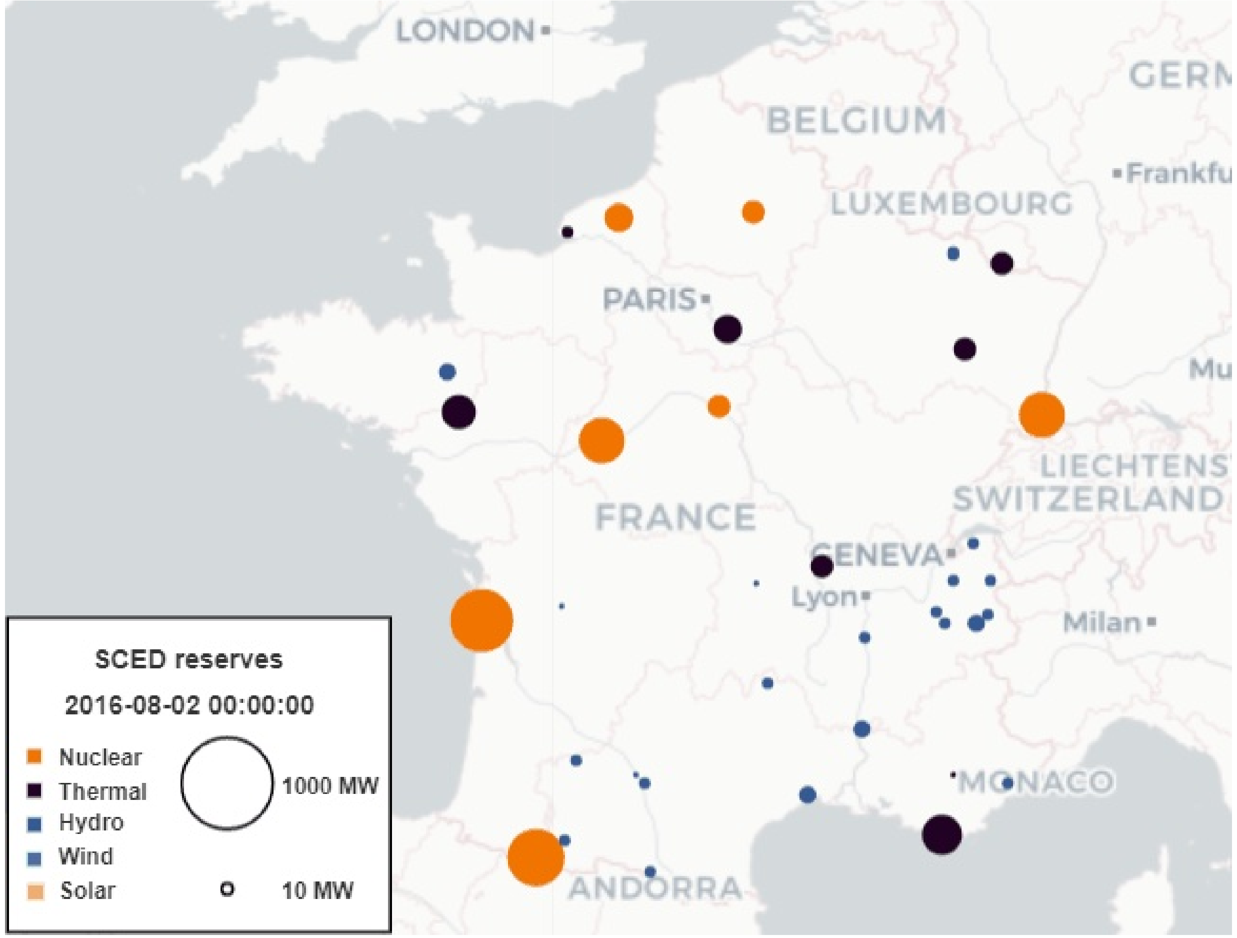

Increased Volatility

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Real-Time Risk Assessment

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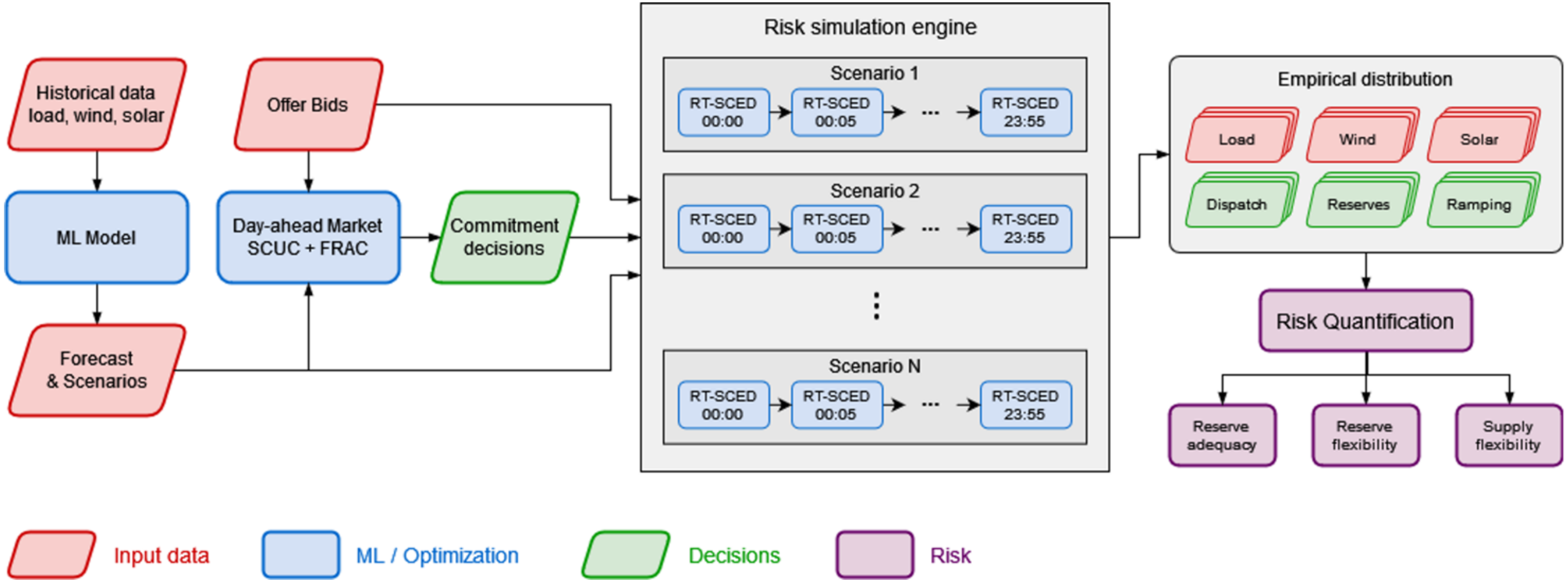
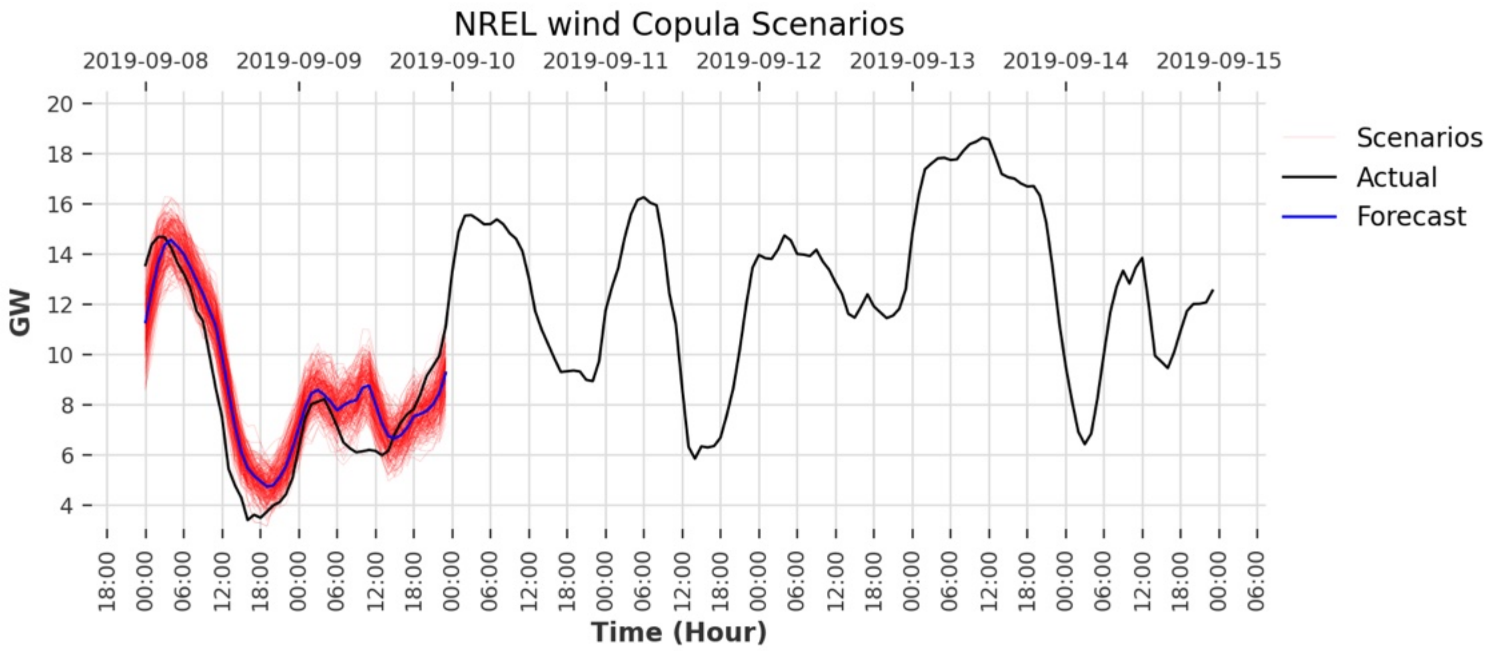
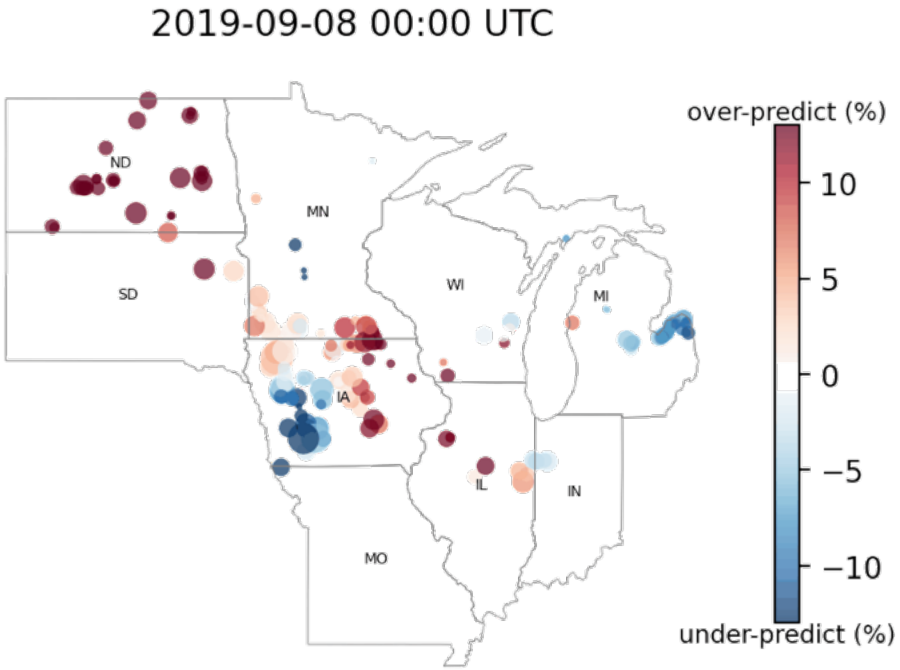


1 Monte-Carlo simulation (24hr) = 288 LPs = ~**15 CPU.min**

Probabilistic Forecasting

- High-dimensional time series forecasting
  - Joint distribution of $O(10^4)$ variables
  - Uncertainty quantification





Data-Driven v.s. Weather-Informed

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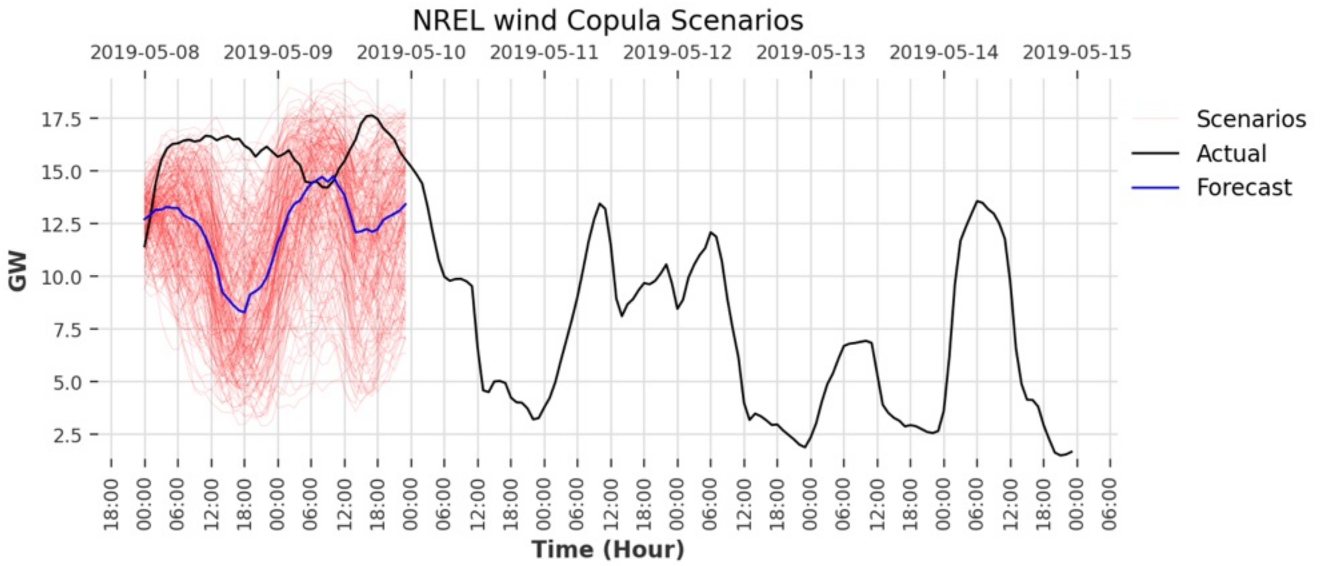
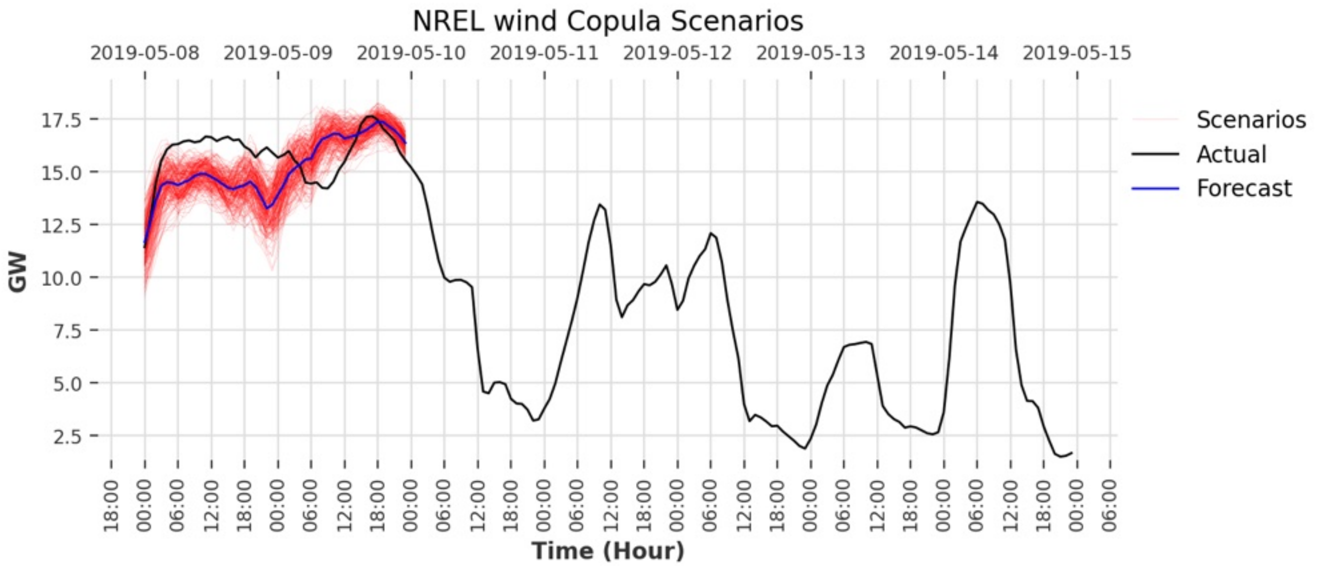


Data Driven



Weather-informed

Forecasting Accuracy

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Probabilistic Forecasting and Scenario Generation

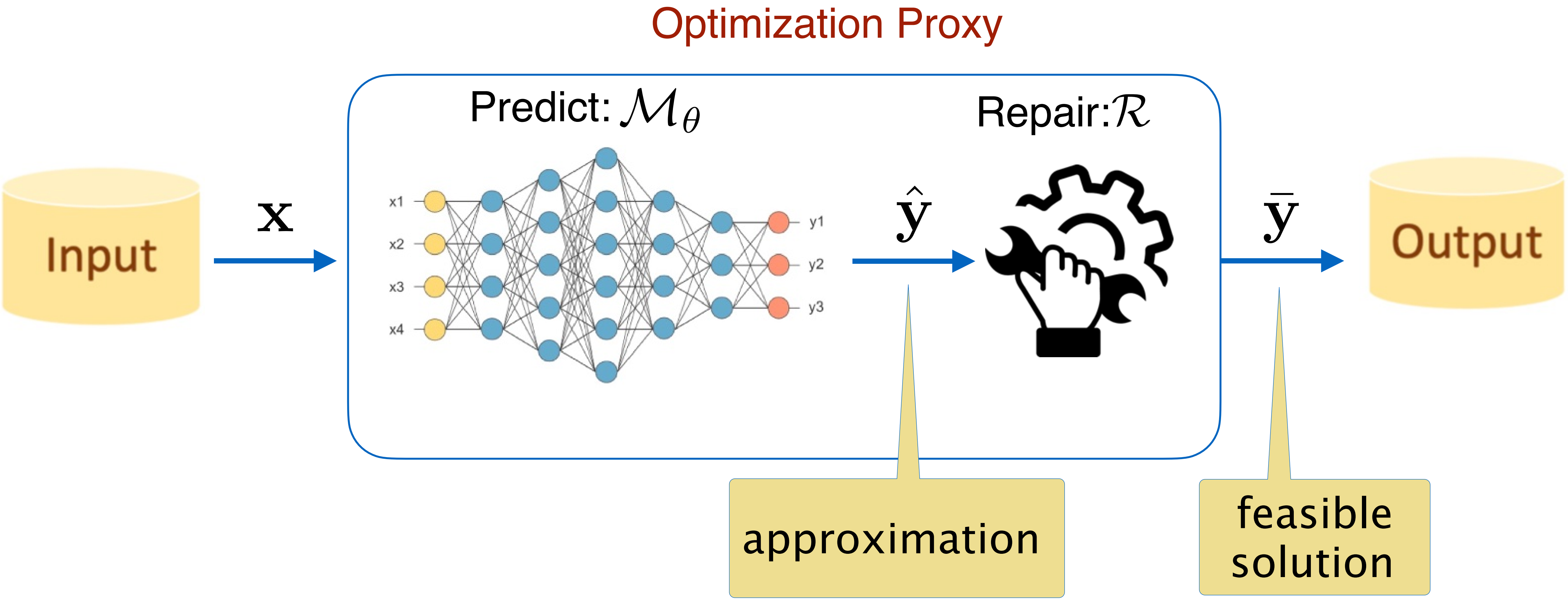
model	load				wind				solar			
	s-sum		ind		s-sum		ind		s-sum		ind	
	NMAE(%)	RMSE	NMAE(%)	RMSE	NMAE(%)	RMSE	NMAE(%)	RMSE	NMAE(%)	RMSE	NMAE(%)	RMSE
ARIMA	4.2%	6316.1	5.2%	1302.4	16.6%	4136.8	28.5%	25.4	9.0%	190.3	12.4%	0.7
Dlinear	2.8%	4211.2	4.2%	1003.1	16.7%	4134.2	26.9%	24.6	7.2%	181.0	10.0%	0.7
Nlinear	3.3%	4964.5	3.9%	994.9	16.2%	4030.6	26.0%	23.9	7.4%	182.5	10.2%	0.7
DeepAR	5.1%	7261.4	6.1%	1428.8	16.8%	4357.0	27.2%	25.3	5.2%	168.9	8.2%	0.7
TFT	2.9%	4473.8	3.7%	954.5	16.7%	4335.3	27.0%	25.7	5.5%	173.3	8.9%	0.7
WI-Dlinear	2.7%	4149.3	3.8%	947.3	9.6%	2615.7	18.5%	18.5	4.8%	130.2	7.3%	0.6
WI-Nlinear	3.0%	4572.3	3.9%	984.6	9.7%	2633.1	18.4%	18.4	5.0%	134.9	7.5%	0.6
WI-DeepAR	1.6%	2461.2	2.3%	596.4	10.3%	2778.3	18.7%	19.4	4.0%	139.7	6.3%	0.6
WI-TFT	**1.1%**	**1702.6**	**1.9%**	**500.4**	**7.9%**	**2152.1**	**16.1%**	**17.0**	**3.1%**	**106.1**	**5.8%**	**0.5**

Table 3
Deterministic Forecast accuracy on MISO dataset

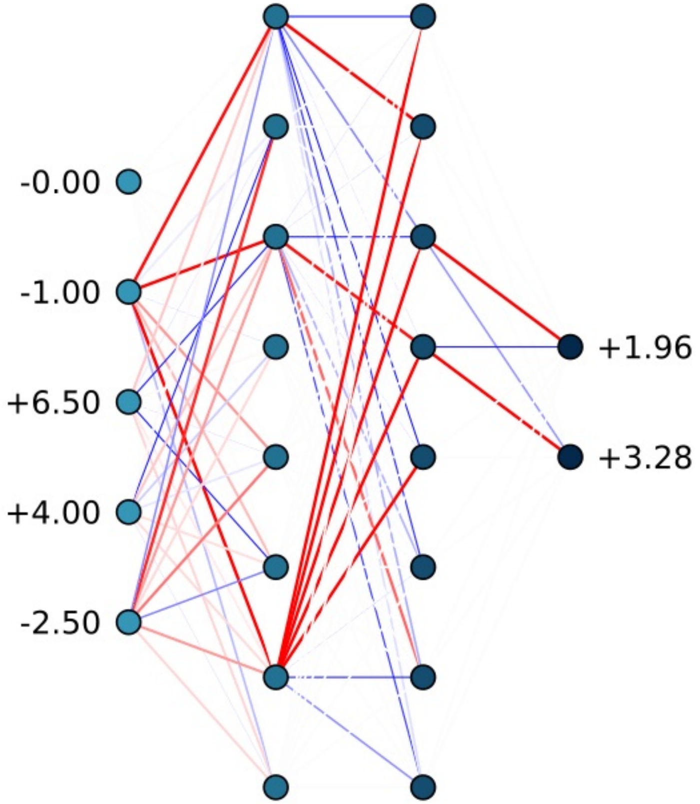
Hanyu Zhang, Reza Zandehshahvar, Mathieu Tanneau and Pascal Van Hentenryck. Weather-Informed Probabilistic Forecasting and Scenario Generation in Power Systems. Applied Energy (to appear)

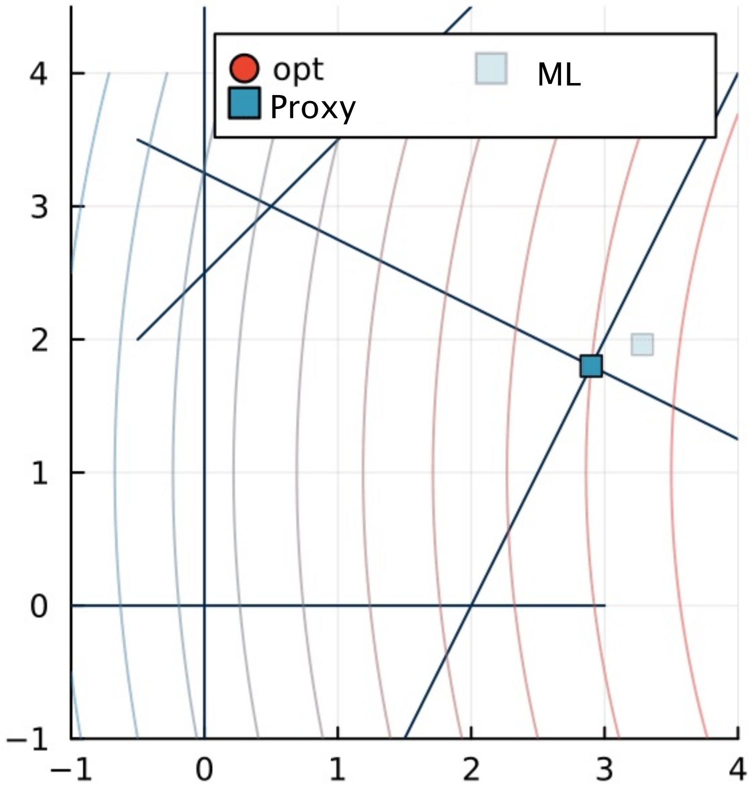
Keeping the lights on!

Optimization Proxy



Optimization Proxy





	MAE	gap	viol
ML	+0.54	−0.29	+1.31
Proxy	+0.00	−0.00	+0.00

Repair Step

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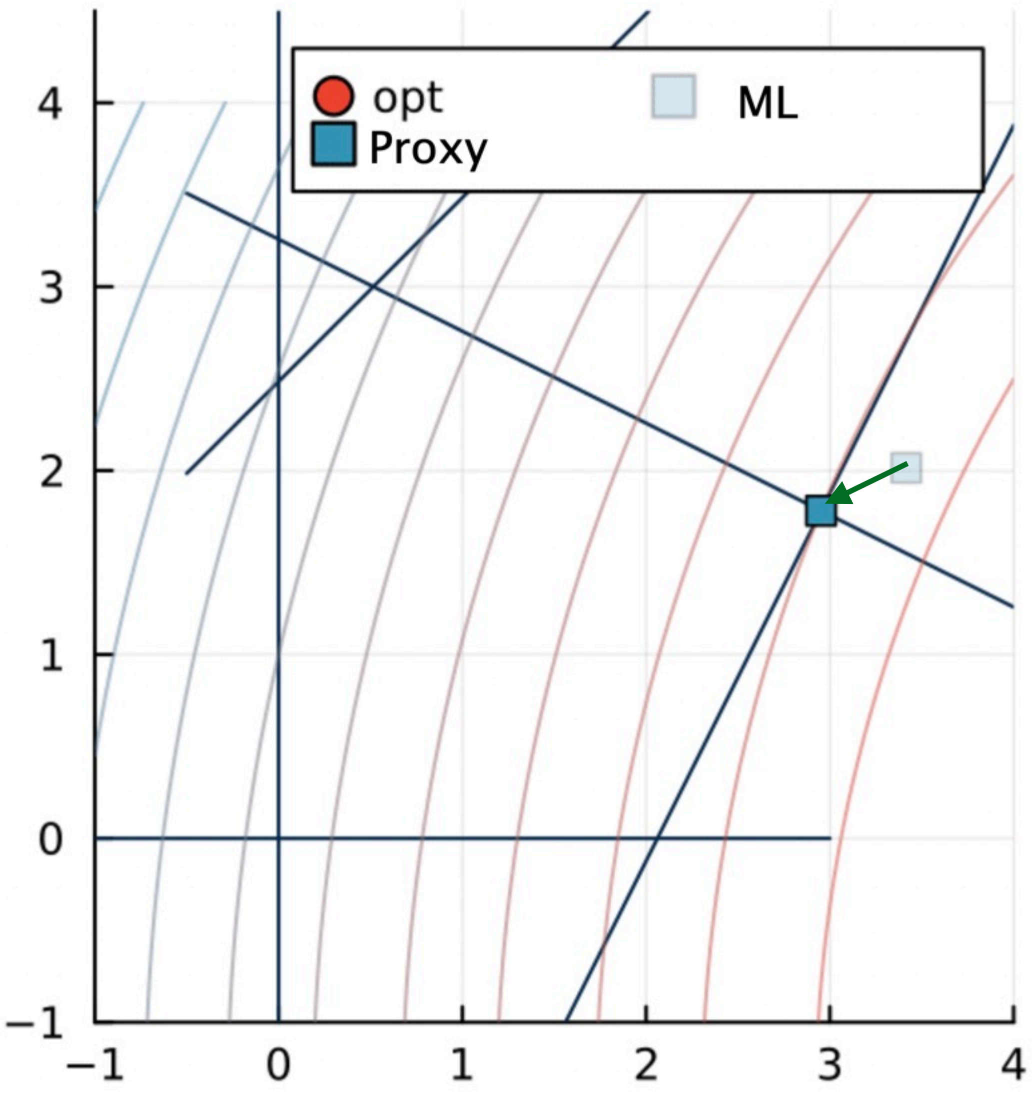

Training the Optimization Proxy

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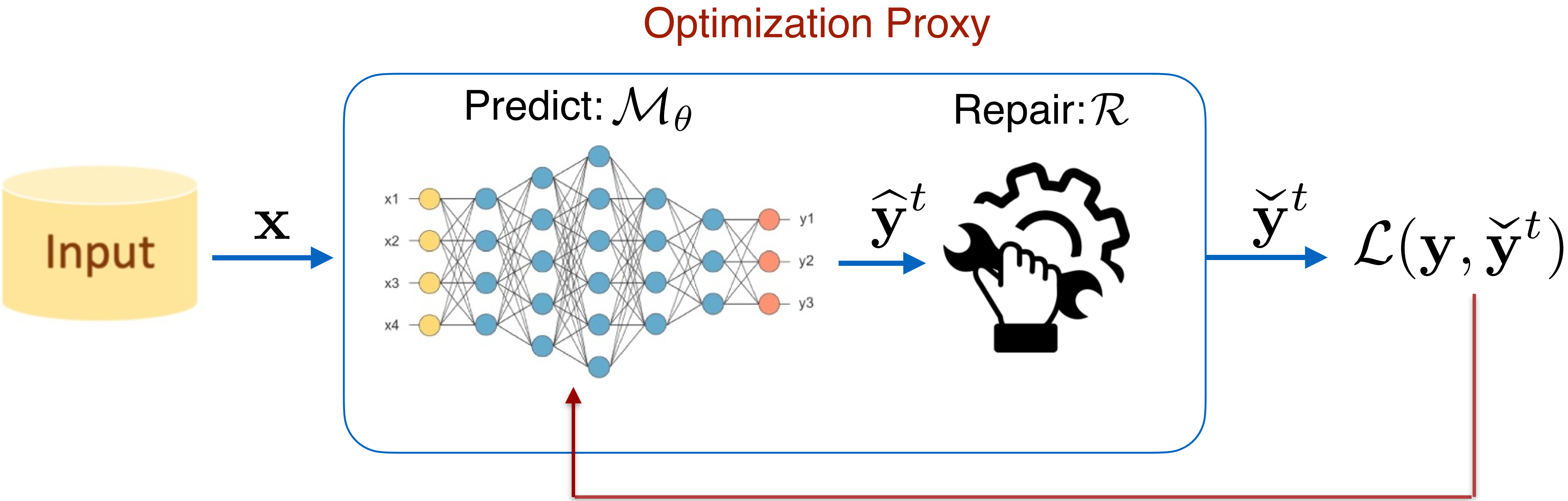
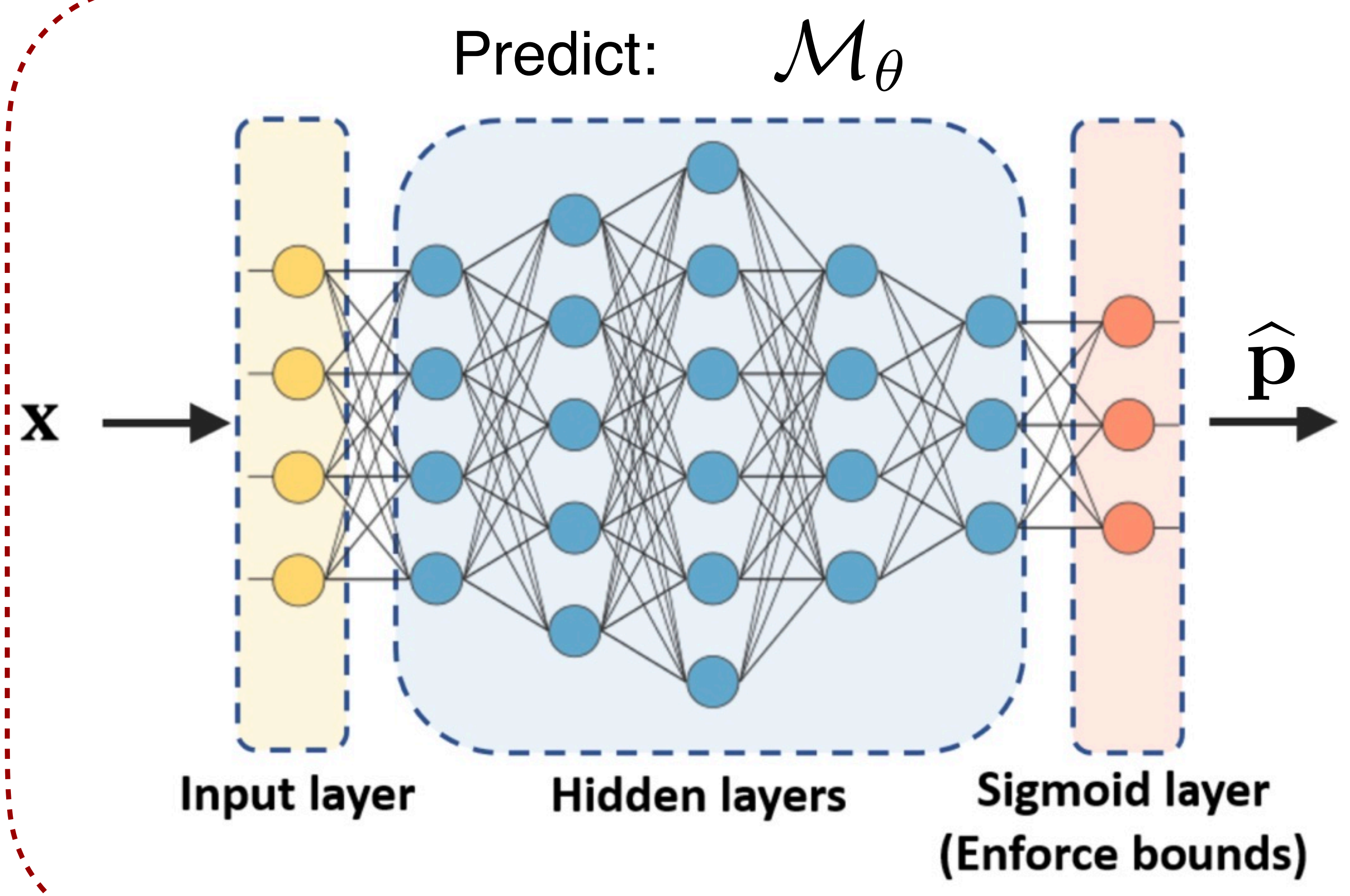


Gradient Step: $\theta^{t+1} = \theta^t - \alpha \dfrac{\partial \mathcal{L}(\mathbf{y}, \check{\mathbf{y}}^t)}{\partial \theta}$

The Primal ED Proxy



Repair: $\mathcal{R}$

Power Balance Layer

$$\tilde{\mathbf{p}} = \begin{cases} (1-\zeta^{\uparrow})\hat{\mathbf{p}} + \zeta^{\uparrow}\bar{\mathbf{g}} & \text{if } \mathbf{1}^\top\hat{\mathbf{p}} < \mathbf{1}^\top\mathbf{d} \\ (1-\zeta^{\downarrow})\hat{\mathbf{p}} + \zeta^{\downarrow}\underline{\mathbf{g}} & \text{otherwise} \end{cases}$$

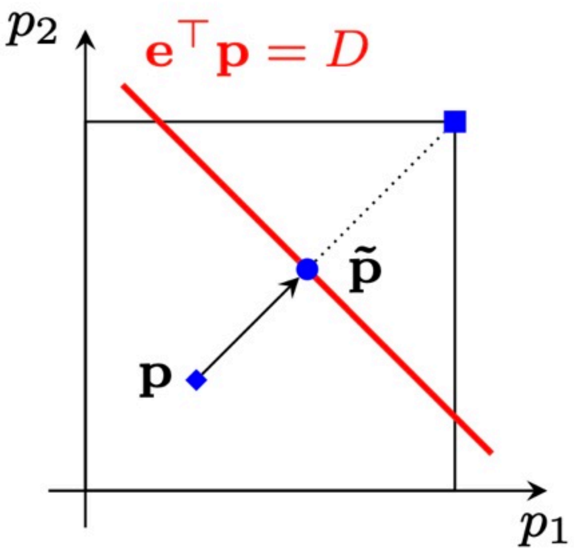
$\downarrow \tilde{\mathbf{p}}$

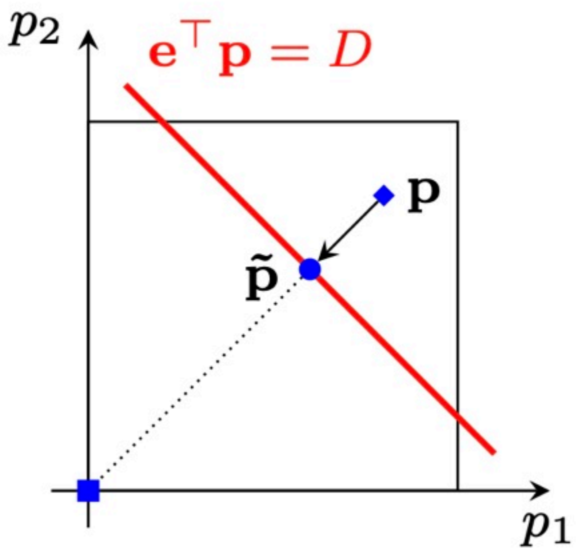
$$\check{p}_g = \begin{cases} \tilde{p}_g + \alpha^{\uparrow}(\bar{p}_g - \bar{r}_g - \tilde{p}_g) & \forall g \in \mathcal{G}^{\uparrow} \\ \tilde{p}_g - \alpha^{\downarrow}(\tilde{p}_g - \underline{p}_g + \bar{r}_g) & \forall g \in \mathcal{G}^{\downarrow} \end{cases}$$

Reserve Layer

$\rightarrow \check{\mathbf{p}}$

Repairing the Power Balance





proportional response

$$\mathcal{P}(\mathbf{p}) = \begin{cases} (1-\eta^{\uparrow})\mathbf{p} + \eta^{\uparrow}\bar{\mathbf{p}} & \text{if } \mathbf{e}^\top \mathbf{p} < D \\ (1-\eta^{\downarrow})\mathbf{p} + \eta^{\downarrow}\mathbf{0} & \text{if } \mathbf{e}^\top \mathbf{p} \geq D \end{cases}$$

Increasing the Reserves

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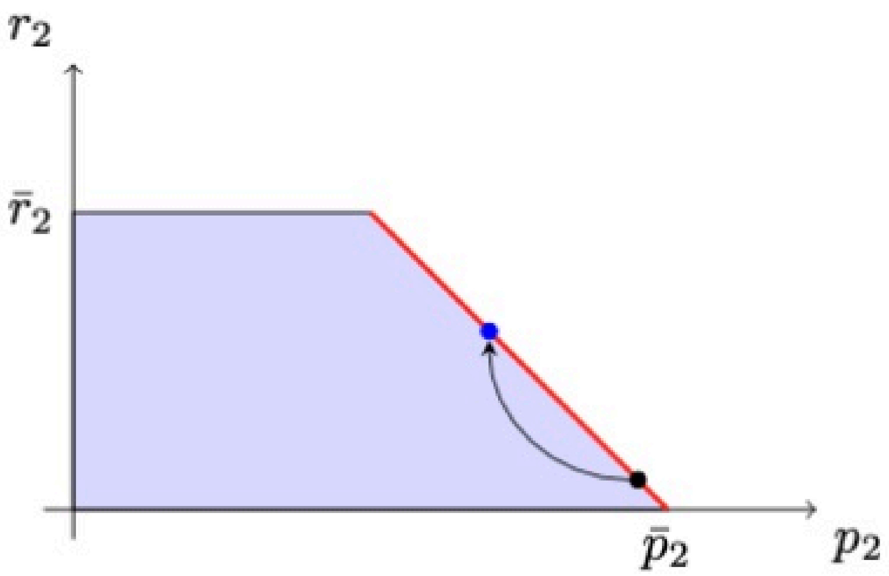

Greedy Generators

$$\mathcal{G}^{\downarrow}$$

Real-Time Risk Assessment

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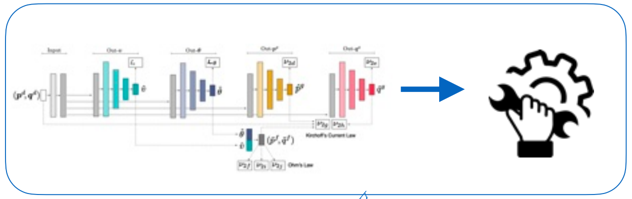
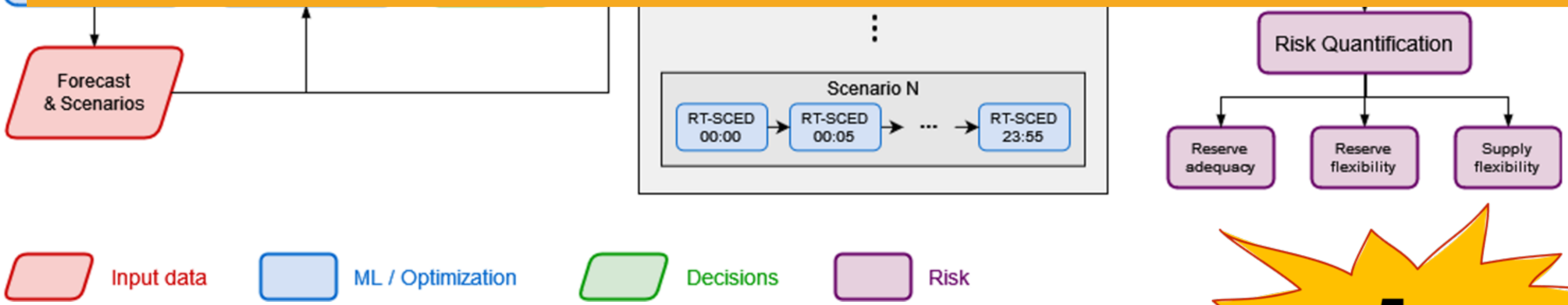
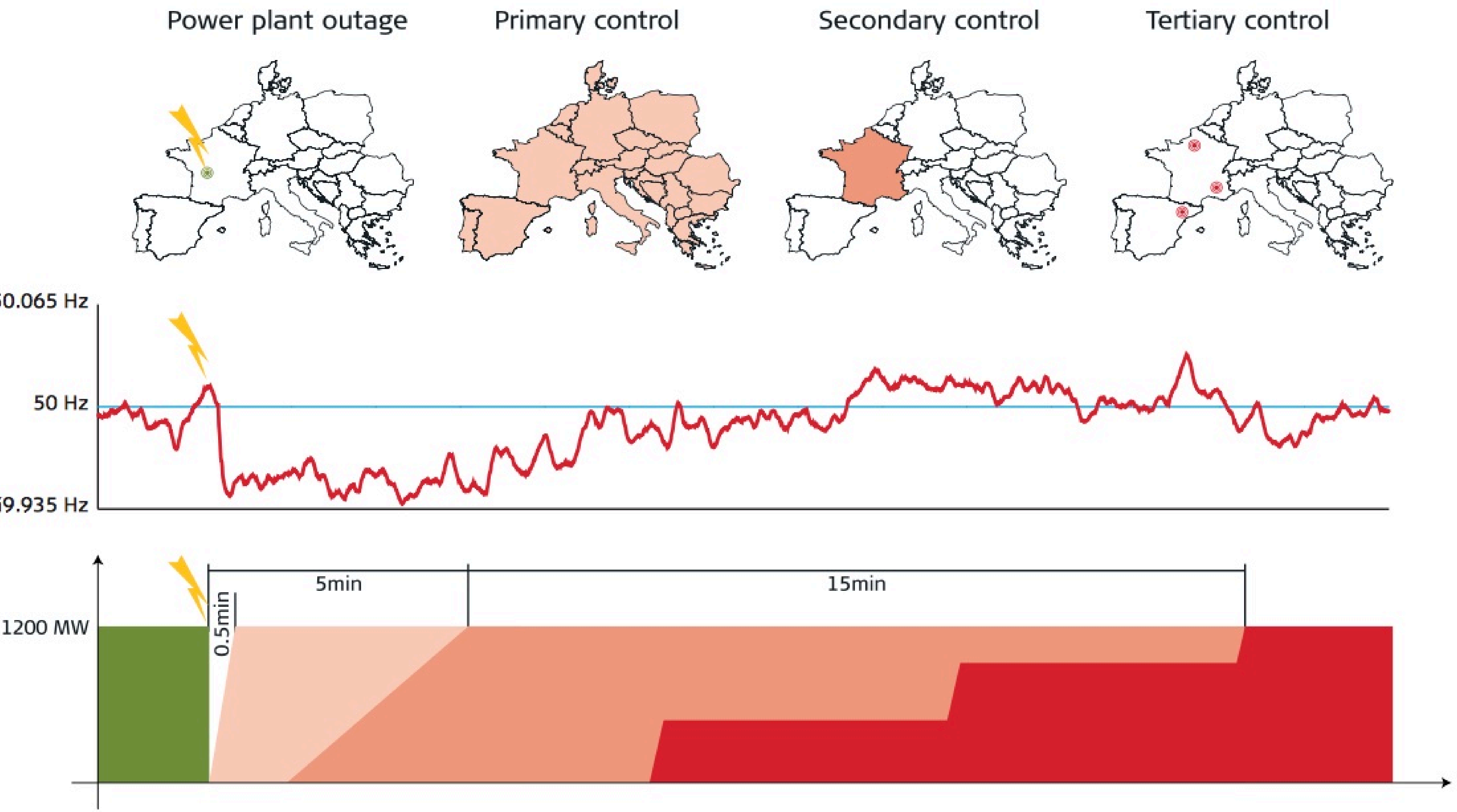


15 min. → 5 sec.



1 Monte-Carlo simulation (24hr) = 288 LPs =

5 s



Power plant outage
Primary control
Secondary control
Tertiary control
50.065 Hz
50 Hz
59.935 Hz
5min
15min
0.5min
1200 MW

Security-Constrained OPF

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$$\min_{\substack{\mathbf{g},\\ [\mathbf{g}_k, \boldsymbol{\rho}_k, n_k]_{k \in \mathcal{K}_g},\\ [\boldsymbol{\eta}_k]_{k \in \{0\} \cup \mathcal{K}_g \cup \mathcal{K}_e}}} \mathbf{c}^\top \mathbf{g} + M_\eta \left(\sum_{k \in \{0\} \cup \mathcal{K}_g \cup \mathcal{K}_e} \|\boldsymbol{\eta}_k\|_1 \right) \quad (1)$$

s. t.:

$$\mathbf{1}^\top \mathbf{g} = \mathbf{1}^\top \mathbf{d} \quad (2)$$

$$\underline{\mathbf{f}} - \boldsymbol{\eta}_0 \leq \mathbf{f} = \mathbf{K}(\mathbf{d} - \mathbf{B}\mathbf{g}) \leq \overline{\mathbf{f}} + \boldsymbol{\eta}_0 \quad (3)$$

$$\underline{\mathbf{g}} \leq \mathbf{g} \leq \overline{\mathbf{g}} \quad (4)$$

$$\mathbf{1}^\top \mathbf{g}_k = \mathbf{1}^\top \mathbf{d} \qquad \forall k \in \mathcal{K}_g \quad (5)$$

$$\underline{\mathbf{f}} - \boldsymbol{\eta}_k \leq \mathbf{f}_k = \mathbf{K}(\mathbf{d} - \mathbf{B}\mathbf{g}_k) \leq \overline{\mathbf{f}} + \boldsymbol{\eta}_k \qquad \forall k \in \mathcal{K}_g \quad (6)$$

$$\underline{g}_i \leq g_{k,i} \leq \overline{g}_i \qquad \forall i \in \mathcal{G}, \forall k \in \mathcal{K}_g, i \neq k \quad (7)$$

$$g_{k,k} = 0 \qquad \forall k \in \mathcal{K}_g \quad (8)$$

$|g_{k,i} - g_i$ … k (9)

$g_i + n_k \gamma_i$ … k (10)

$g_{k,i} \geq \hat{g}_i \rho$ … k (11)

$\underline{\mathbf{f}} - \boldsymbol{\eta}_k \leq$ … (12)

$$\boldsymbol{\eta}_k \geq 0 \qquad \forall k \in \{0\} \cup \mathcal{K}_g \cup \mathcal{K}_e \quad (13)$$

$$n_k \in [0, 1] \qquad \forall k \in \mathcal{K}_g \quad (14)$$

$$\rho_{k,i} \in \{0, 1\} \qquad \forall i \in \mathcal{G}, \forall k \in \mathcal{K}_g, i \neq k \quad (15)$$

Contingencies

Power Balance in the Contingencies

thermal limits

Case Studies

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A. Velloso, P. Van Hentenryck, and S. E. Johnson. An exact and scalable problem decomposition for security-constrained optimal power flow. *Electric Power Systems Research* 195(June): 106677, 2021.

Inference Times in ms

2.5 hours → < 10 ms

4917_goc	3720.33	8033.86	13316.93	7	10.98	16
6515_rte	4648.31	9560.78	92430.47	4	6.65	10

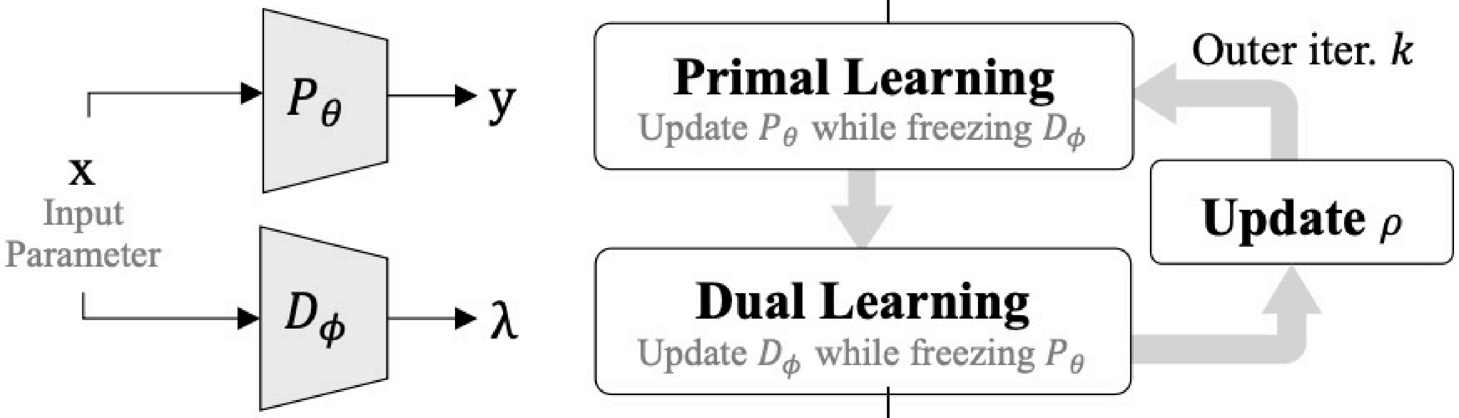
Over 2.5 hours

8@GPU
5.163
6.917
7.956
13.486

4917_goc	[illegible]	[illegible]	[illegible]	31.775
6515_rte	823.016	6767.474	10.576	51.9370

Self-Supervised Primal-Dual Learning

$$\theta^{t+1} = \operatorname*{argmin}_{\theta} \frac{1}{n} \sum_{i \in [n]} f_{\mathbf{x}_i}(\mathbf{y}_i) + +D_{\phi^t}(\mathbf{x}_i)^T \, \mathbf{h}_{\mathbf{x}_i}(\mathbf{y}_i) + \frac{\rho}{2} \mathbf{1}^\top \mathbf{h}_{\mathbf{x}_i}(\mathbf{y}_i)^2$$



$$\phi^{t+1} = \operatorname*{argmin}_{\phi} \frac{1}{n} \sum_{i \in [n]} \left\| D_\phi(\mathbf{x}_i) - D_{\phi^t}(\mathbf{x}_i) + \rho \, \mathbf{h}_{\mathbf{x}_i}(P_{\theta^{t+1}}(\mathbf{x}_i)) \right\|$$

The Primal and Dual Networks

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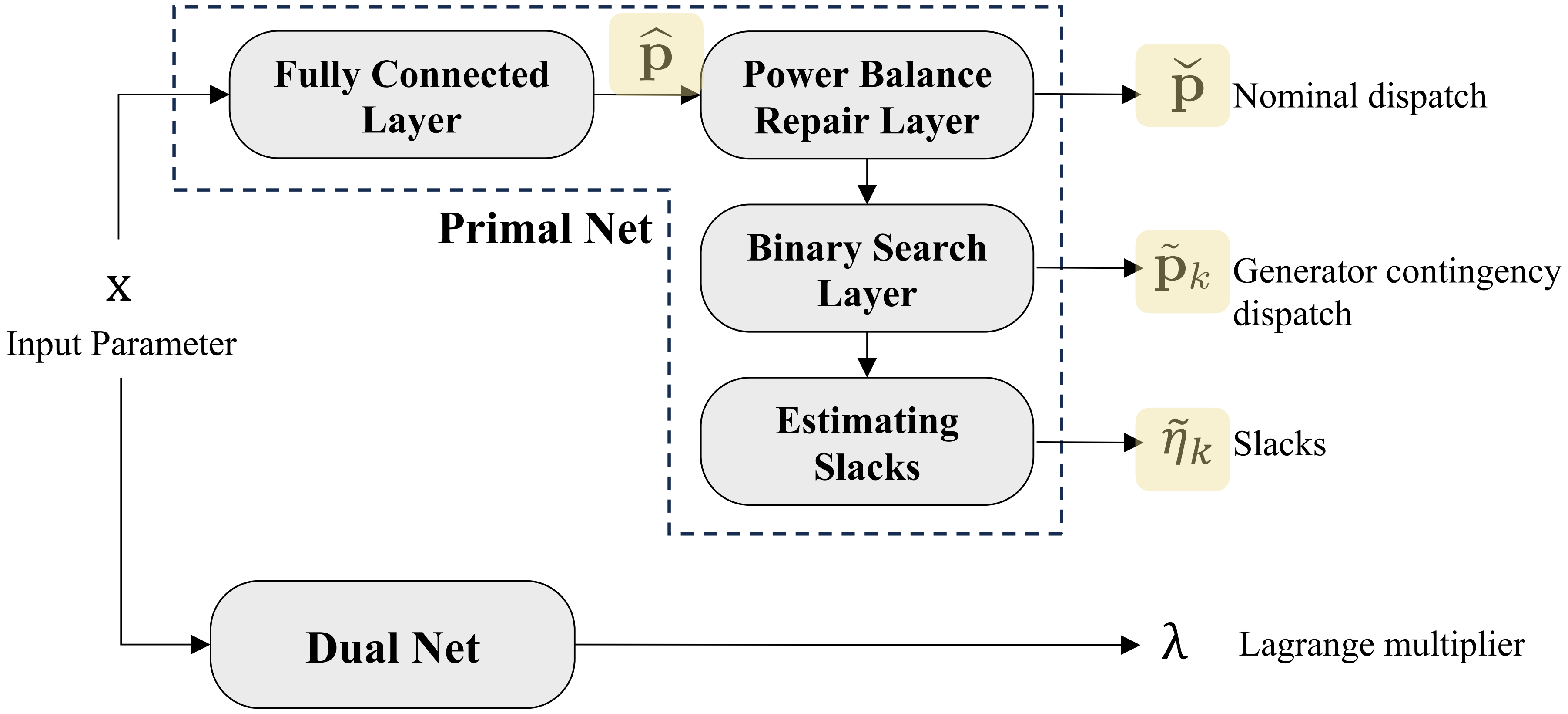

[Submitted on 29 Nov 2023 (v1), last revised 27 Apr 2024 (this version, v2)]

Self-Supervised Learning for Large-Scale Preventive Security Constrained DC Optimal Power Flow

Seonho Park, Pascal Van Hentenryck


FINISH

AI is Ready
for Critical Power Systems Applications

AI is the Key Technology Enabler
for Critical Power Systems Applications

The Challenges for AI in Engineering

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