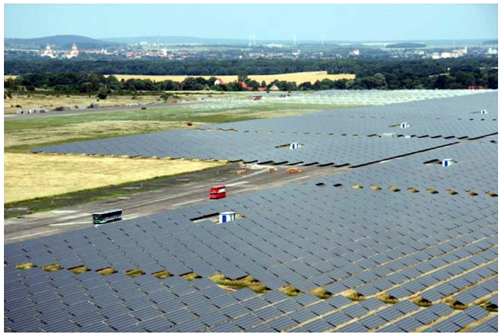
RISK-AWARE MARKET CLEARING

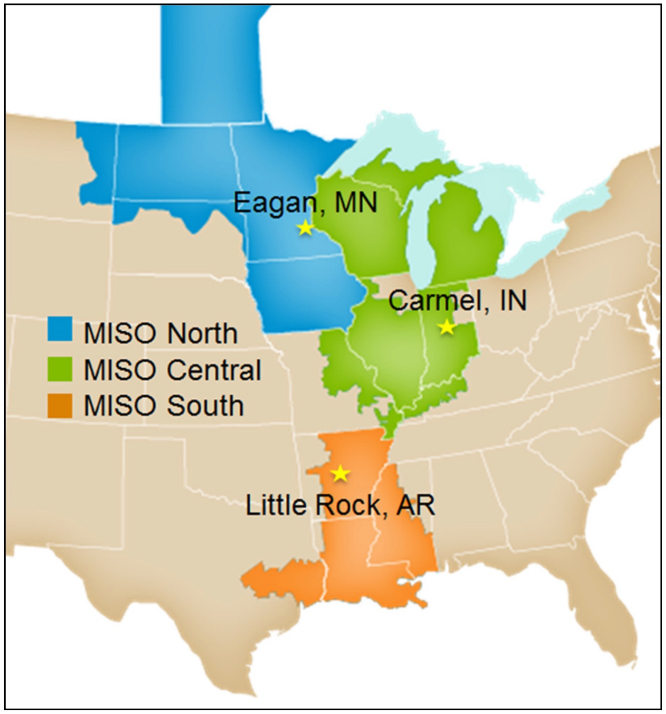
Pascal Van Hentenryck

Collaboration between Georgia Tech, MISO, and Vanderbilt Uni.

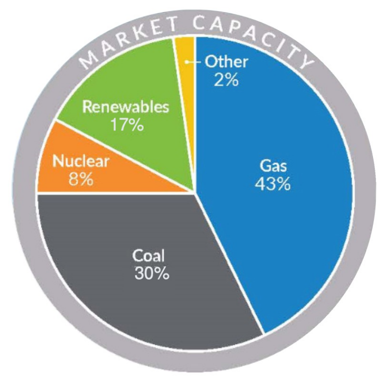
The Challenge



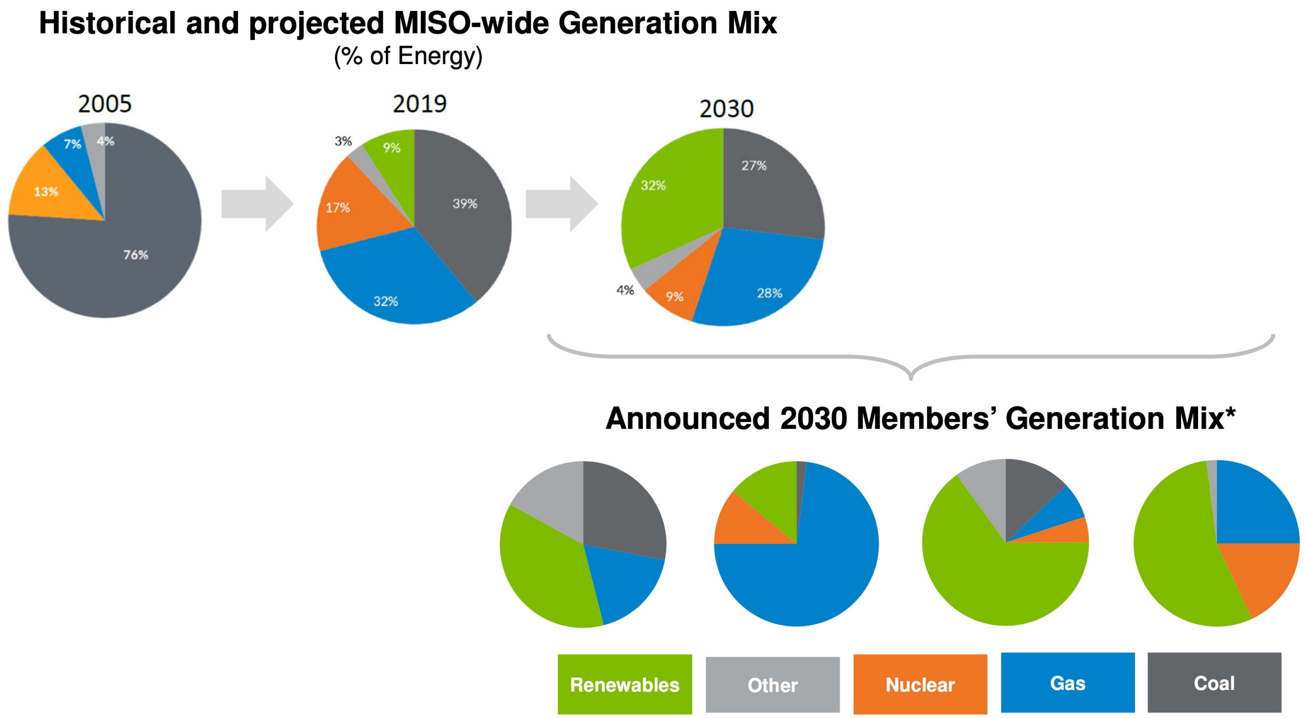
MISO Today



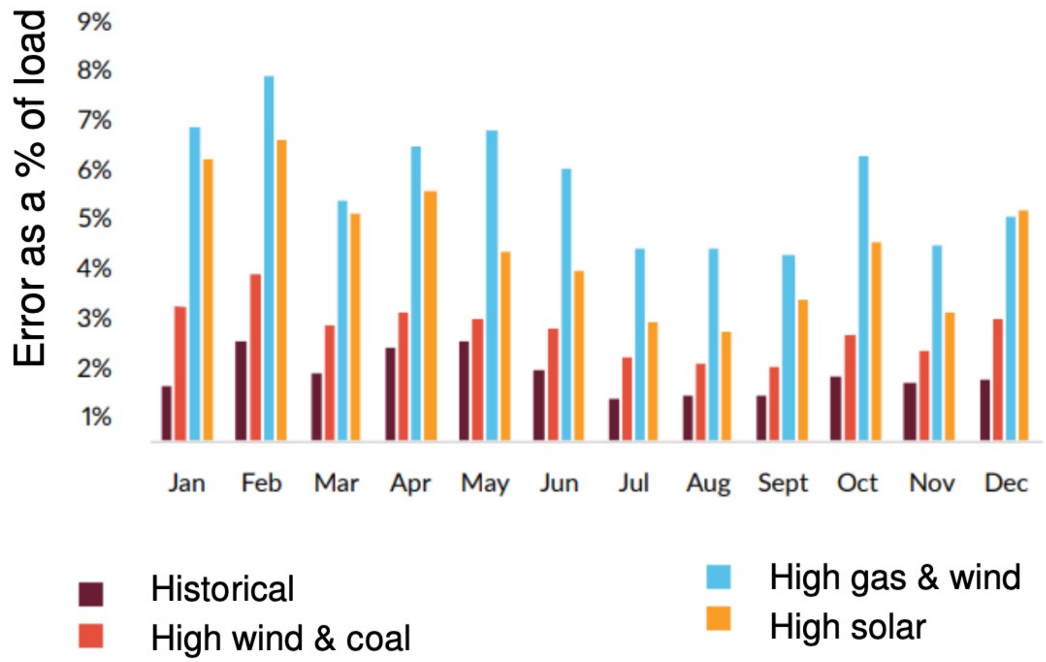
MISO by-the-numbers	
Transmission	71,800 miles
Generation Capacity	177,760 MW
Peak Summer System Demand	127,125 MW
Customers Served	42 Million



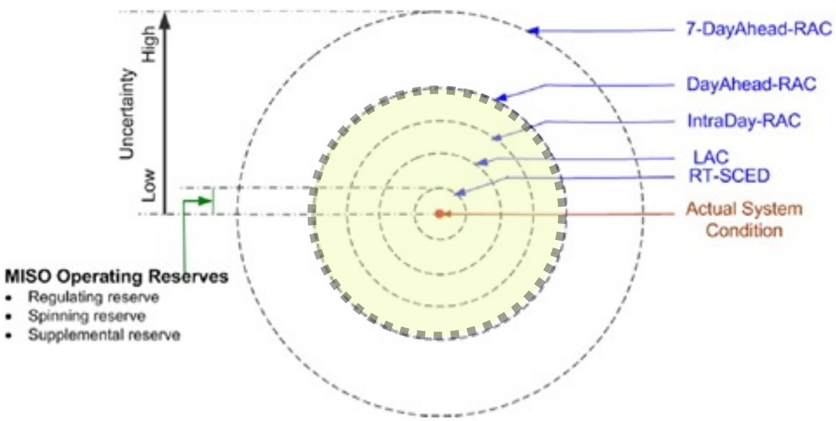
MISO Tomorrow

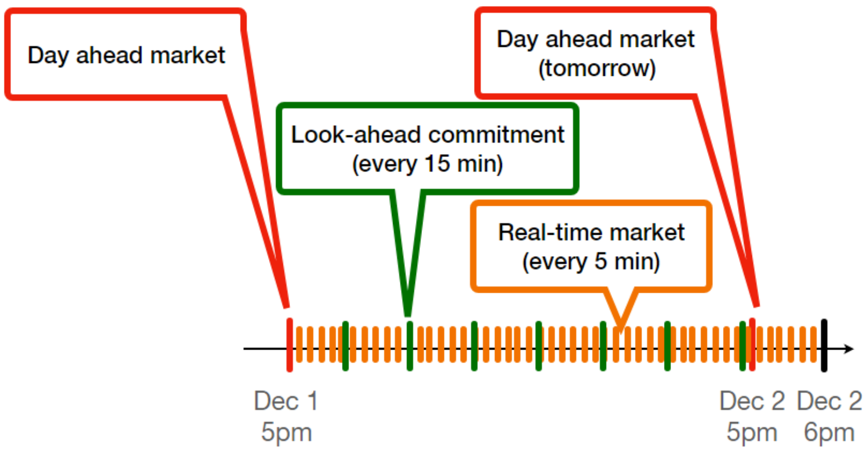


Increasing Prediction Error



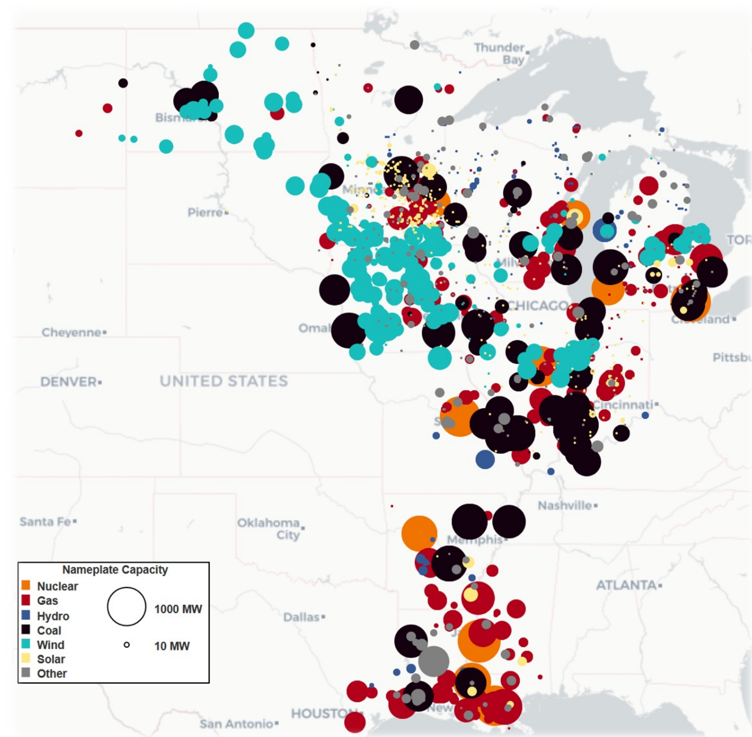
End-to-End Risk Management





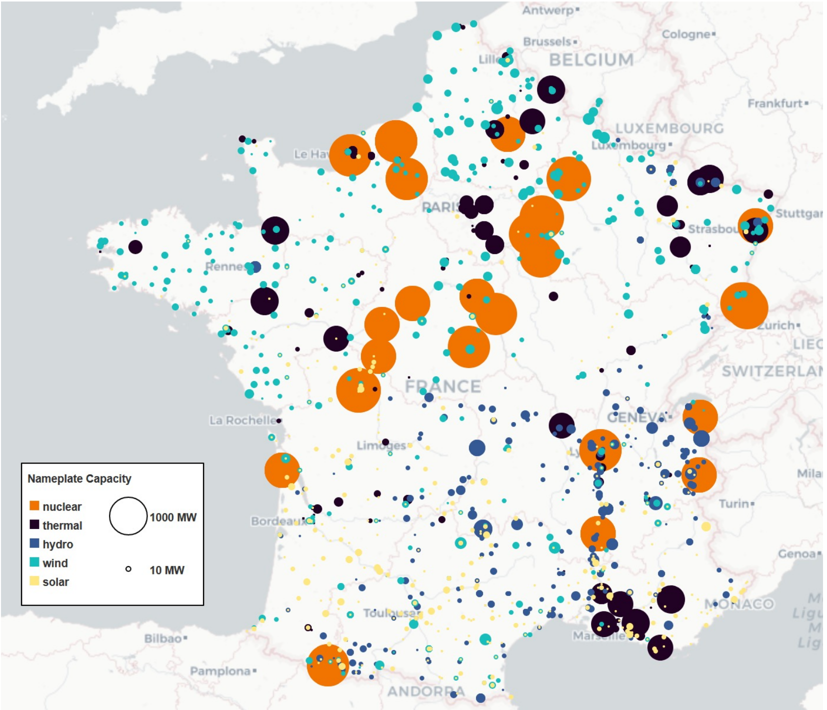
RAMC Datasets

- Time series (CUI)
  - Load (LBA level) + wind (unit-level)
  - 5min granularity, 04/2017 – 04/2019
  - Weather data from USAF database (public)
- Optimization instances (CUI)
  - Generator data + subset of transmission lines
  - DA-SCUC: one week of data
  - LAC: 672 instances
    - 96 instances on 01/29/2019
    - 572 instances on 09/15 – 09/20/2018

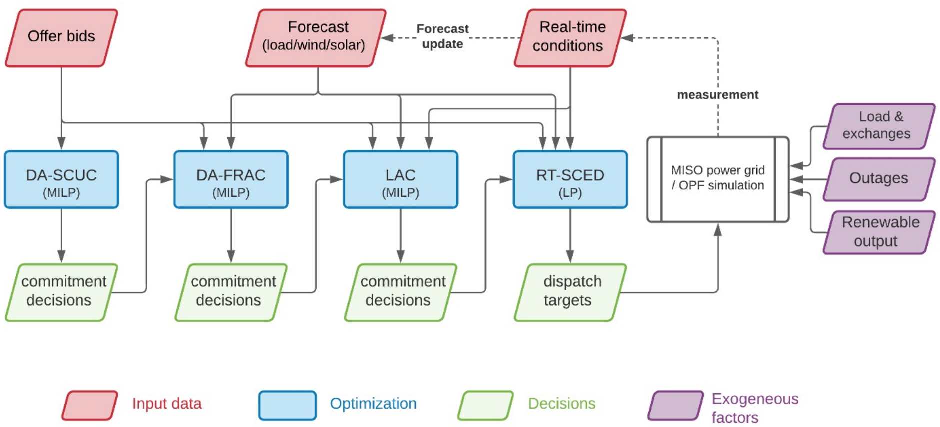


RAMC Datasets (RTE)

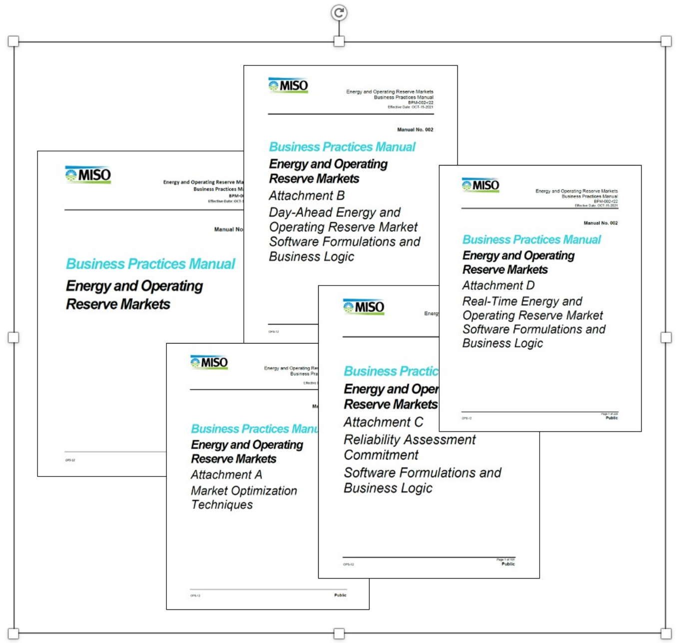
- Grid
  - Full network topology (AC)
  - Additional units to match 2018 system
- Time series & Forecasts
  - Regional load/wind/solar every 30min
  - Day-ahead forecasts (hourly) for load/wind/solar
  - Disaggregated to bus-level components
- Economic data
  - Generator offer data matched from PJM bids



MISO Market Clearing Pipeline



- RAMC Digital twin
  - MISO's technical documentation: >1000 pages
  - RAMC codebase (opt. only): >20,000 lines of Julia
  - Deterministic and stochastic formulations



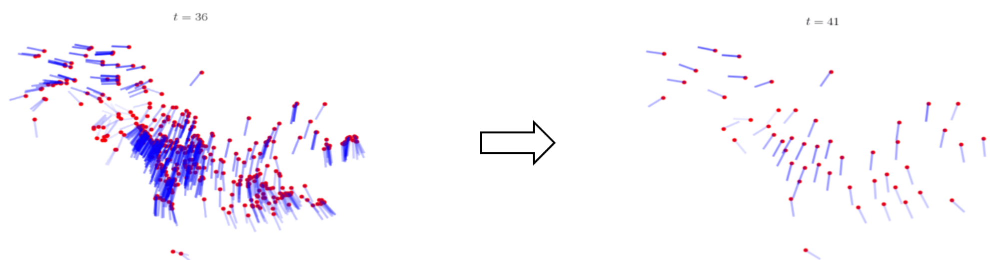
Forecasting

- Predictive models needed for…
  - Load / Wind / Solar predictions
  - Point-forecasts & uncertainty quantification

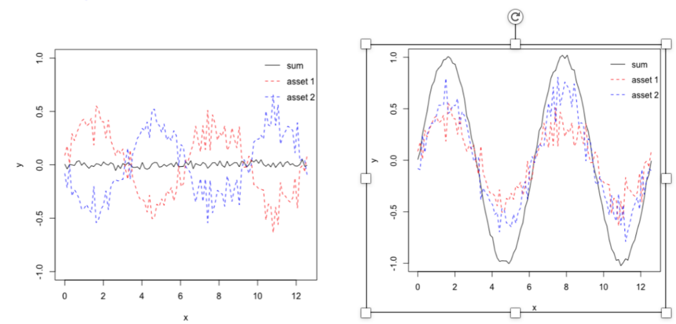
- RAMC leverages
  - Asset-bundling tools
  - Spatio-temporal models
  - Uncertainty quantification and scenario-generation
  - Down-sampling with support points

Asset Bundling

- Reduce dimensionality
  - Fewer dimensions → smaller models, faster training



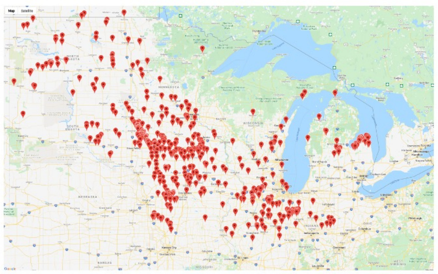
- Bundled time series are easier to learn
  - Lower variance, lower **intermittency**
  - Positive impact on learning models

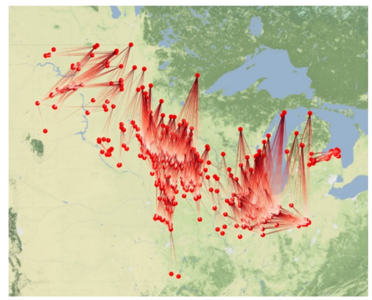


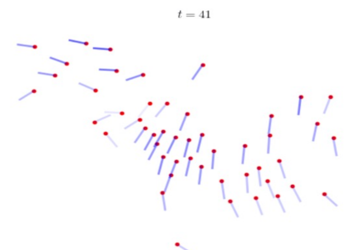
RAMC Risk-Aware Market Clearing Project

Forecasting & Uncertainty quantification

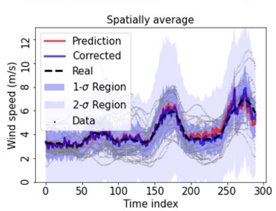
- Spatio-temporal forecasting models
  - Dynamic graph captures interactions between windfarms

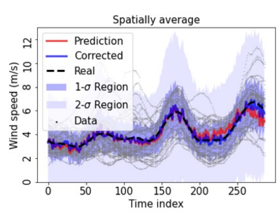


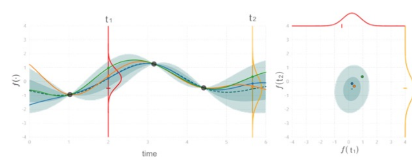


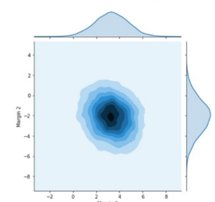


- Uncertainty quantification + scenario generation
  - Spatio-temporal distributions; Gaussian processes; Gaussian Copula



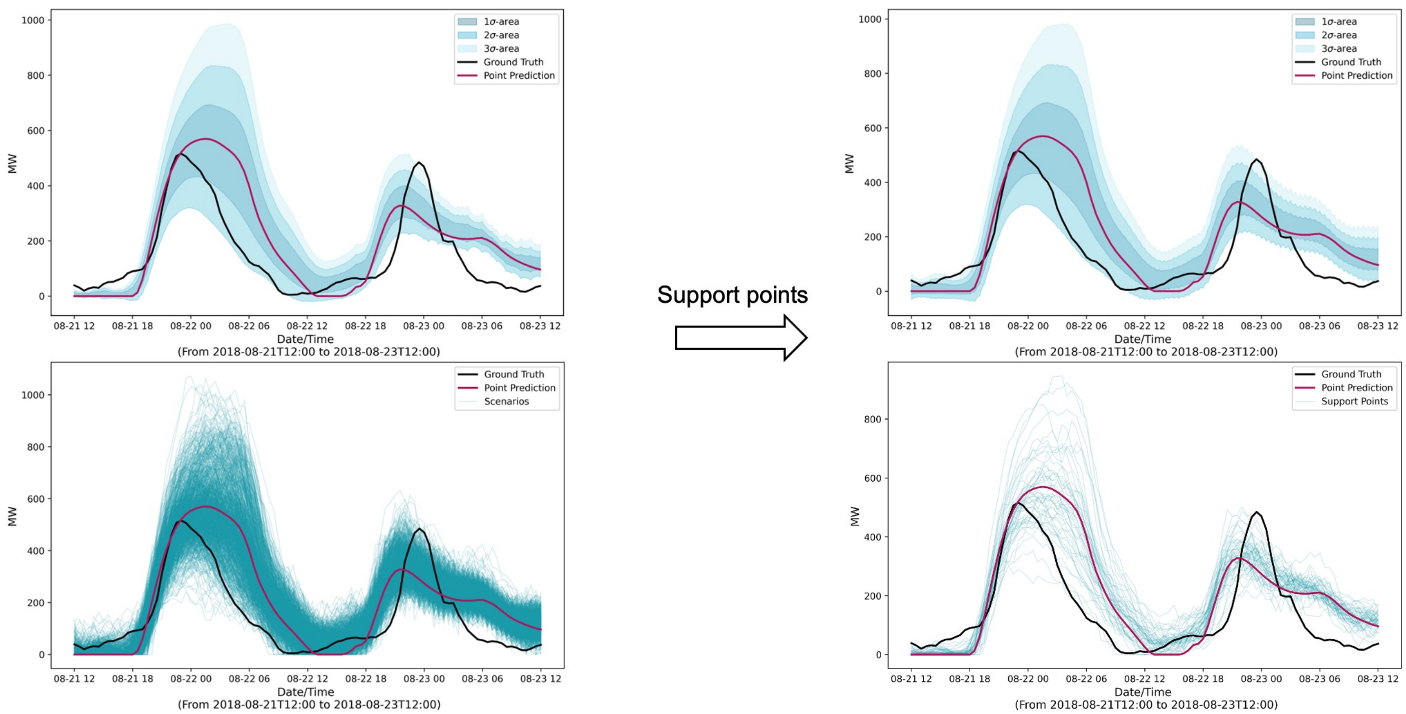






Support points

- Scenario reduction with support points



Similar distribution…

… with much fewer samples

Stochastic Formulations

- Two-stage stochastic programming (TSSP) formulations
  - 1st stage ($\boldsymbol{x}$)
    - FRAC/LAC: commitment
    - SCED: energy/reserve dispatch at t=1
  - 2nd stage ($\boldsymbol{y}$, per scenario)
    - FRAC/LAC: energy/reserve dispatch
    - SCED: energy/reserve dispatch at t>1

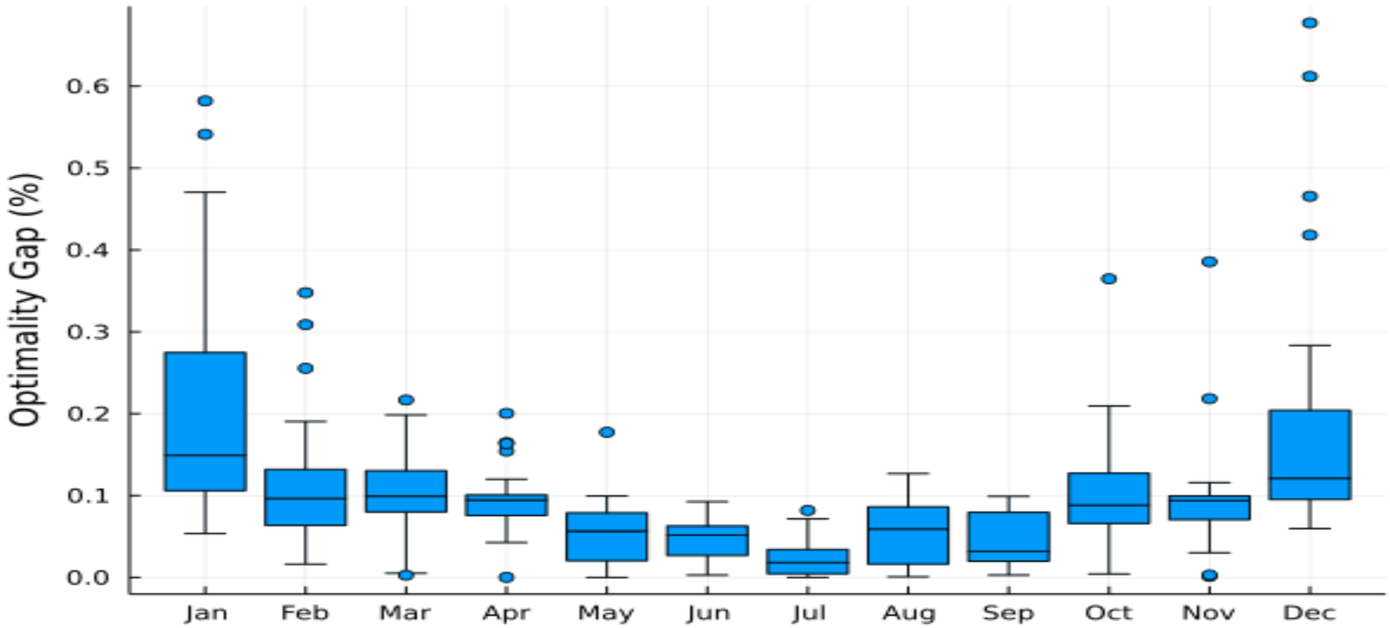
$$\min_{\boldsymbol{x},\boldsymbol{y}} \quad c^T \boldsymbol{x} + \sum_s p_s \times q_s^T \boldsymbol{y}_s$$ Total expected cost

$$s.t. \quad A\,\boldsymbol{x} \geq b, \boldsymbol{x} \in X$$ First-stage constraints

$$T\,\boldsymbol{x} + W_s\,\boldsymbol{y}_s \geq h_s \quad \forall s$$ Second-stage constraints

Stochastic FRAC

Distribution of SFRAC optimality gaps at 40min (RTE, 2018)



Stochastic FRAC

Season	FRAC Cost	FRAC (VPI)	RDH Cost	RDH (VPI)	SFRAC Cost	SFRAC (VPI)	PFRAC Cost
Spring	332.13	(13.78%)	289.68	(1.11%)	287.21	(0.29%)	286.37
Summer	35.56	(2.19%)	34.80	(0.05%)	34.80	(0.05%)	34.78
Fall	879.22	(17.52%)	729.67	(0.61%)	727.00	(0.25%)	725.16
Winter	692.42	(21.82%)	546.18	(0.90%)	544.40	(0.58%)	541.25

Learning Optimization Proxies for Large-scale SCED

Loads, renewable generation, economic bids, commitment decisions …

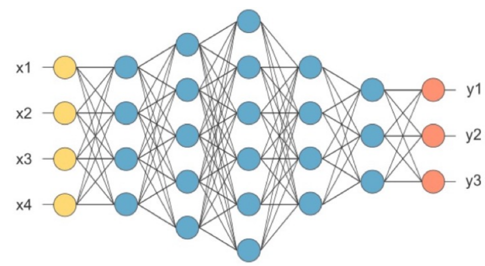
Optimal energy/reserve dispatch

SCED Optimization Model

Solved every 5 minutes

Learning Optimization Proxies for Large-scale SCED

Loads, Renewable generations, Economic bids, Commitment decisions …



Machine Learning Model

Predict in milliseconds

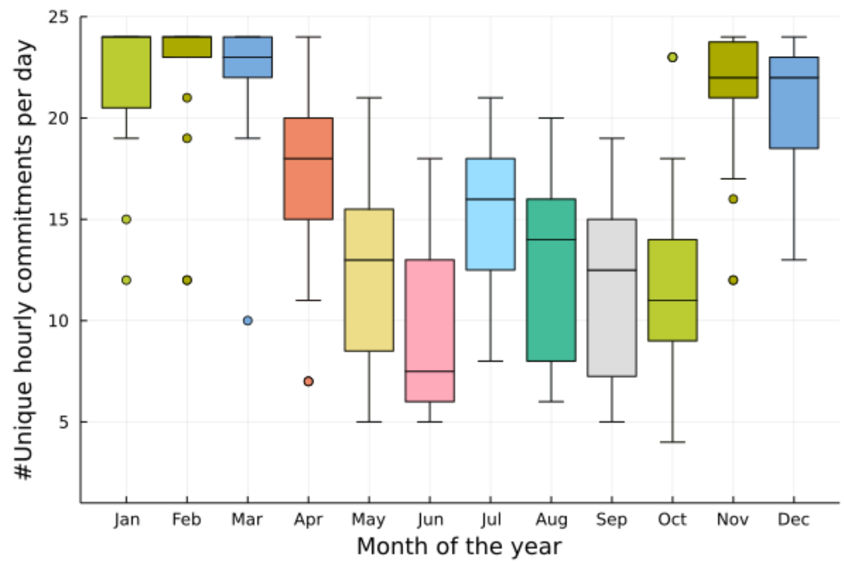
Optimal energy/reserve dispatch

- Limitations:
  - Small academic test systems
    - **We focus on systems with 6,500 buses or more**
  - Industrial formulation
  - Dataset from over simplified simulation;
    e.g., only considers the change of loads
    - ❌ spatio-temporal correlations of loads
    - ❌ renewable generation
    - ❌ economic bids
    - ❌ commitment decisions

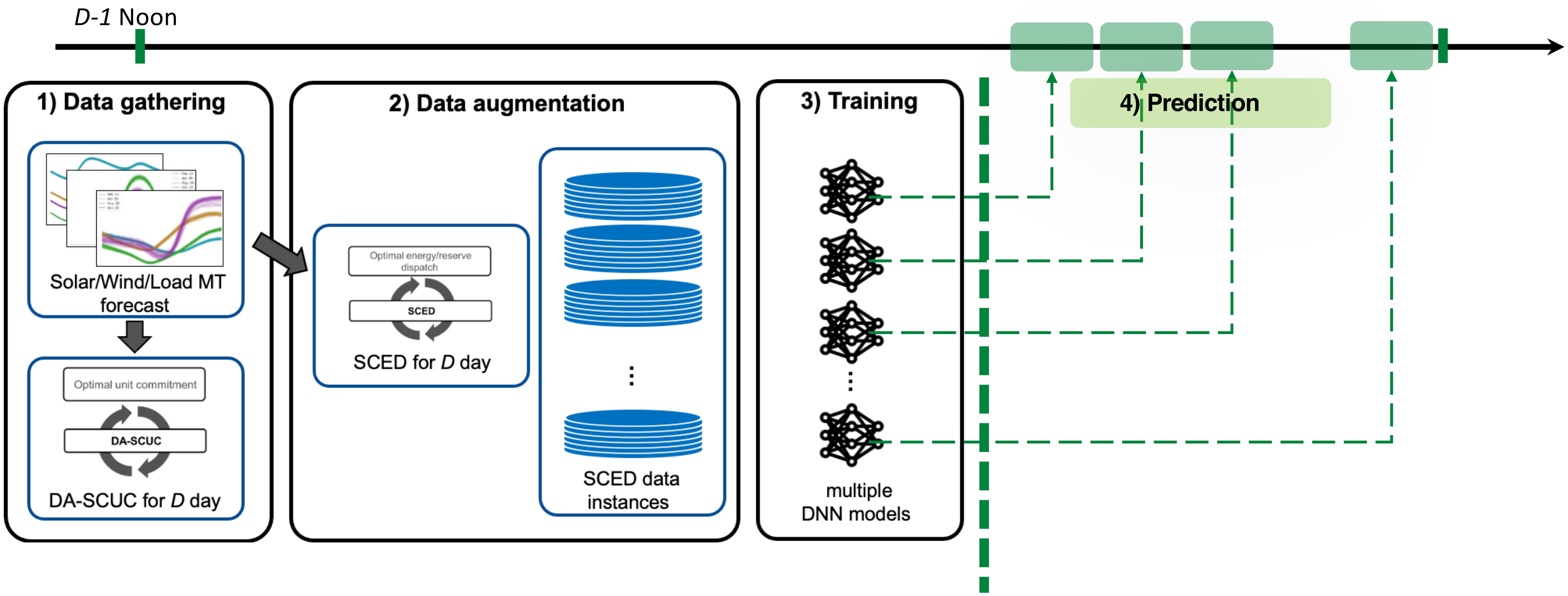
The Challenge

High variability in commitment decisions

- Annual seasonal patterns of the commitment decisions
- Total of 5380 different hourly commitments across 8760 hours in 2018
- Combinatorial explosion of commitment decision → adverse effect on ML model



Just-in-Time Learning Pipeline



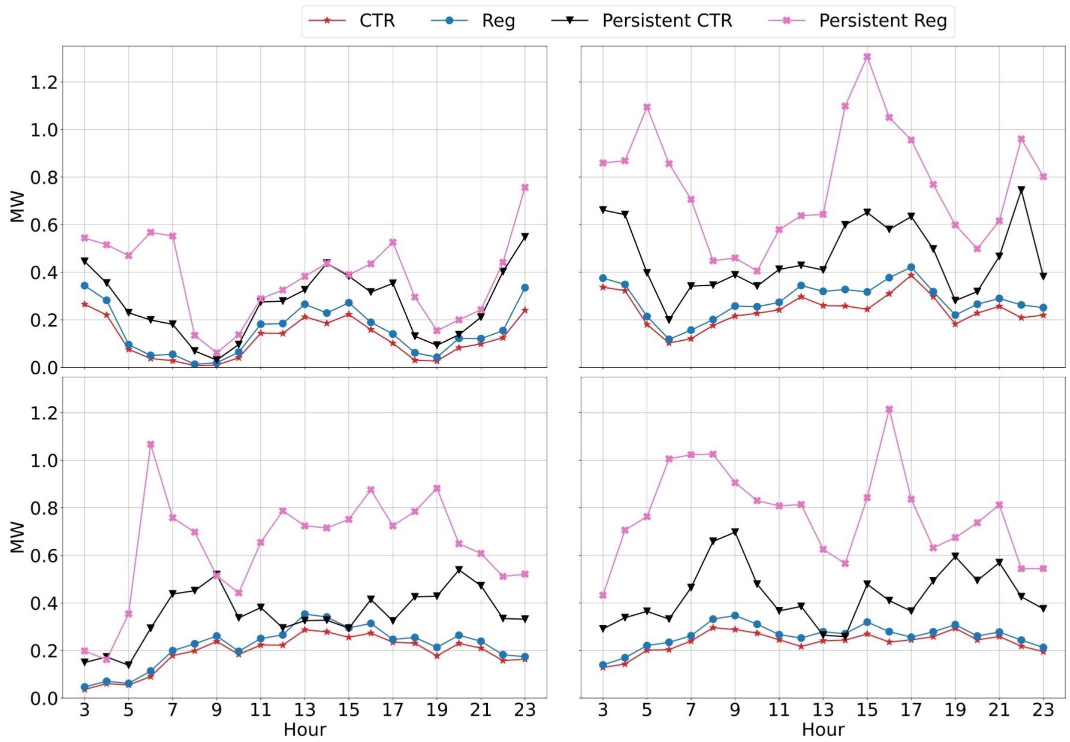
Just-in-Time SCED Learning

- CTR model
  - Classifier $C_{w_1}: \mathbb{R}^d \rightarrow \{0,1\}^{2g}$
    - Determine whether each generator is at upper/lower limit or neither
  - Regressor $C_{w_2}: \mathbb{R}^{d+2g} \rightarrow \mathbb{R}^g$
    - Regress the active power dispatch
    - Additional $2g$ in the input is induced by the classifier
- Loss functions
  - Classification: binary cross entropy loss
  - Regression: MAE loss
- Trainable parameters: around 4 millions

< Input features>

Feature	Size	Source
Loads	L	Load forecasts
Cost of generators	G	Bids
Cost of reserves	$2G$	Bids
Previous solution	G	SCED
Commitment decisions	G	SCUC
Reserve Commitments	G	SCUC
Generator min/max limits	$2G$	Renewable forecasts
Line losses factor	$2B+1$	System

Just-in-Time SCED Learning



Just-in-Time SCED Learning

Date	Method	Small	Medium	Large	All
Feb. 12	Naive Reg	0.122	0.465	1.602	0.374
	Naive CTR	0.084	0.333	1.128	0.262
	Reg	0.057	0.188	0.654	0.153
	CTR	**0.043**	**0.141**	**0.535**	**0.117**
Apr. 05	Naive Reg	0.242	0.345	7.480	0.772
	Naive CTR	0.197	0.220	4.374	0.463
	Reg	0.149	0.152	2.553	0.282
	CTR	**0.105**	**0.110**	**2.291**	**0.241**
Aug. 26	Naive Reg	0.097	0.256	7.447	0.637
	Naive CTR	0.080	0.149	4.045	0.352
	Reg	0.054	0.124	2.454	0.218
	CTR	**0.034**	**0.064**	**2.220**	**0.190**
Oct. 23	Naive Reg	0.176	0.535	8.425	0.778
	Naive CTR	0.140	0.341	4.596	0.434
	Reg	0.106	0.192	2.724	0.263
	CTR	**0.076**	**0.145**	**2.525**	**0.235**

†Small: 0-10MW; Medium: 10-100MW; Large: $>$100MW

Up to 37% improvement for small generators and 48% for medium generators;

CTR have 0.59% and 0.34% MAPE for medium and large generators;

Just-in-Time SCED Learning

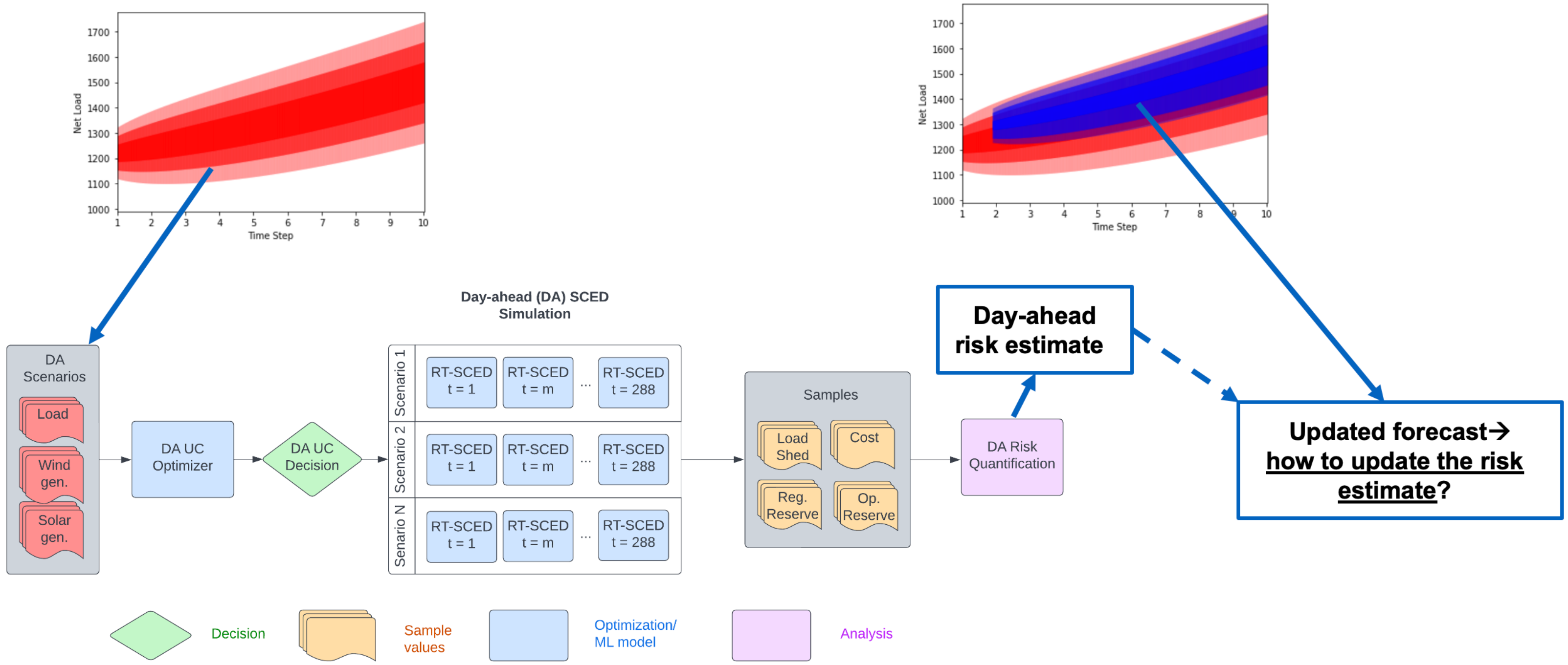
- 4 orders of magnitude faster

Method	Average Time	Maximum Time
SCED Optimization	~16s	85s
CTR Model	< 1e-3s	< 1e-3s

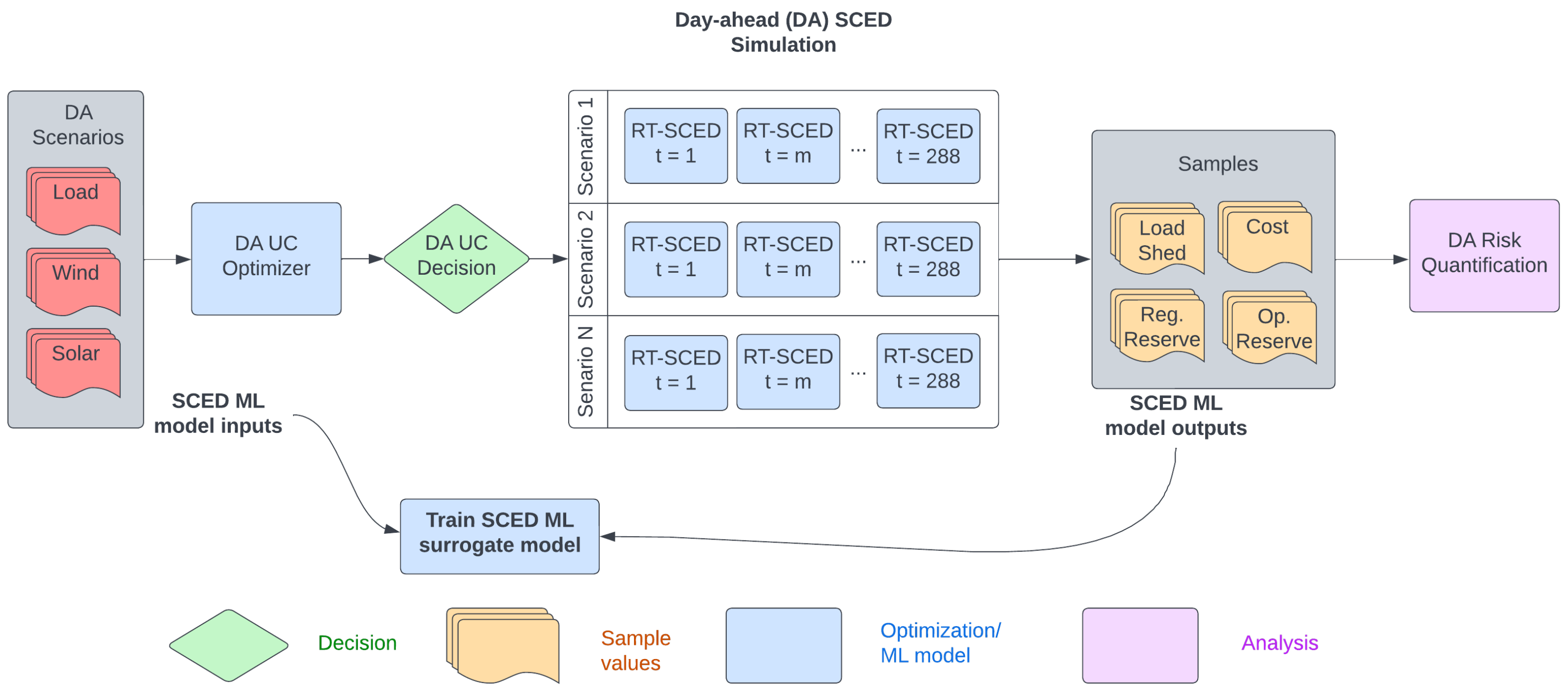
Risk Assessment

Day-ahead forecast for t = 1, 2 .. 24 (red)

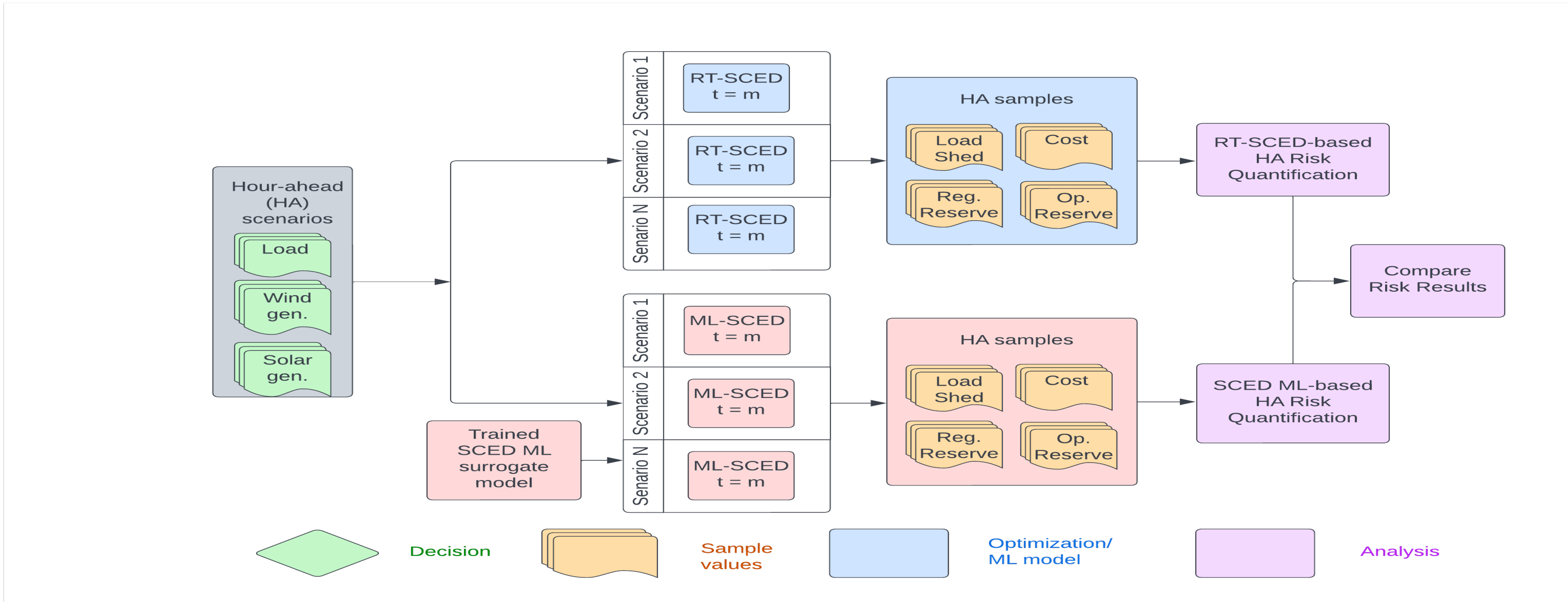
Updated forecast at t = 1 for t = 2,3 .. 24 (blue)



Incremental Risk Assessment



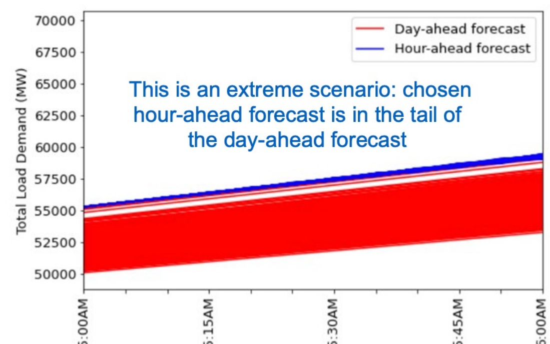
Incremental Risk Assessment



SCED Risk Learning

- RTE grid
  - Divided into 12 regions (zones)
  - Three stochastic variables per zone (wind/solar generation and load)
  - Perform system level SCED risk estimation
- For the FRAC UC portfolio, update the risk for the next hour
  - Two time periods considered in this example: 5:00am – 10:00 am, 4:00 pm–9:00 pm (morning and evening peak hours)
  - Predict system cost, regulating reserve, operating reserve, and load shed with both ML surrogate and full RT-SCED optimization
  - Using predicted QOIs, compute the risk

https://en.wikipedia.org/wiki/Regions_of_France



RAMC Risk-Aware Market Clearing Project

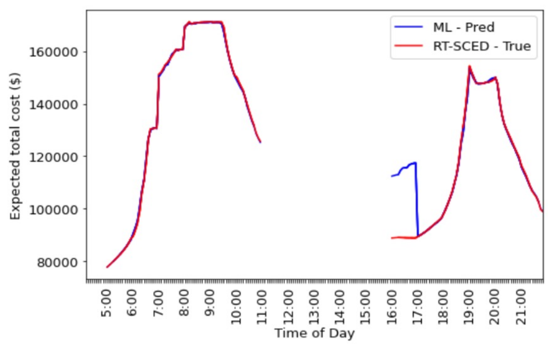
SCED Risk Learning

- **Model inputs (40):**
  - 12 x zonal wind/load/solar values
  - Total wind/load/solar values
  - Hour of day
- **Model outputs (4):**
  - Cost
  - Regulating reserve
  - Operating reserve
  - Load shed
- **Training data:**
  - 288 x 2500 MC samples from day-ahead risk assessment → 288 x 2500 MC input-output samples
  - 70-30 train-test split
  - **Random forest regression**

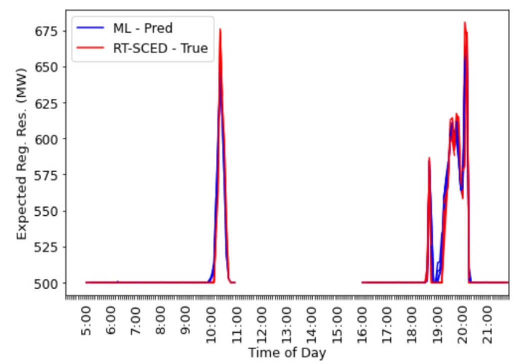
Model Validation

QOI	MAE	Range
Cost	$ 271	$ [67,000, 174,237]
Reg. Reserve	2.2 MW	[500, 888] MW
Operating Reserve	36 MW	[500, 3300] MW
Load Shed	0.94 MW	[0, 2810] MW

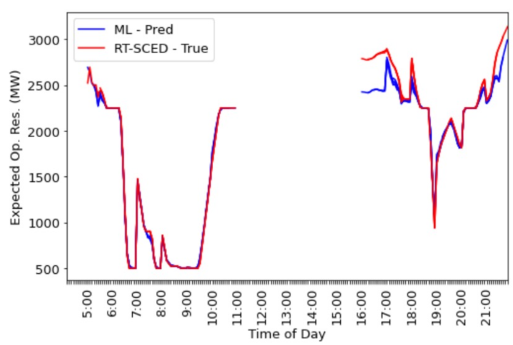
SCED Risk Learning: Accuracy



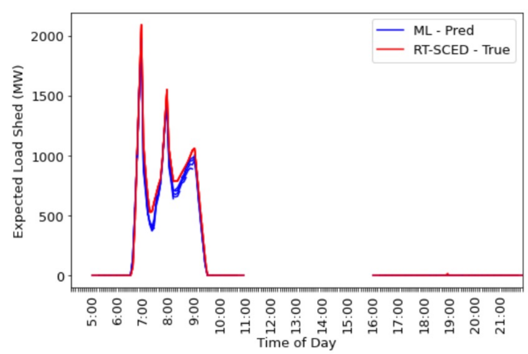
Expected cost



Expected regulating reserve

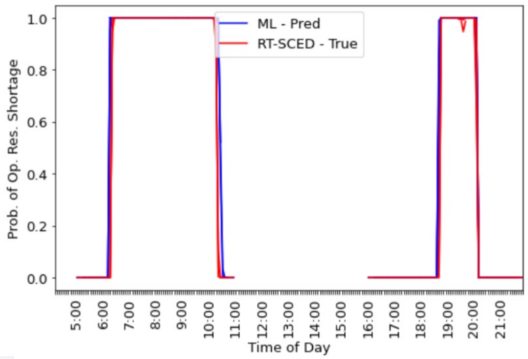


Expected operating reserve

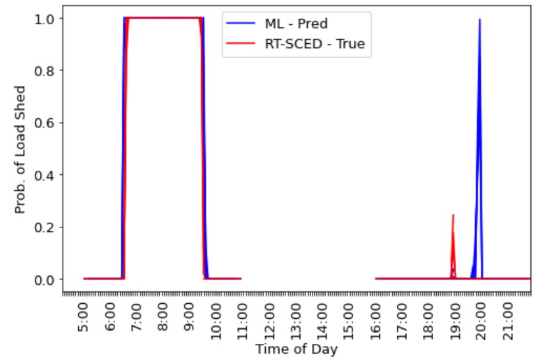


Expected load shed

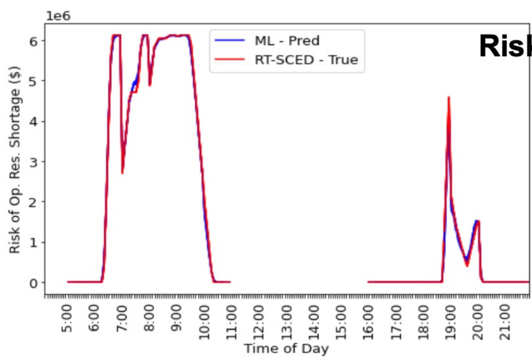
SCED Risk Learning: Profiles



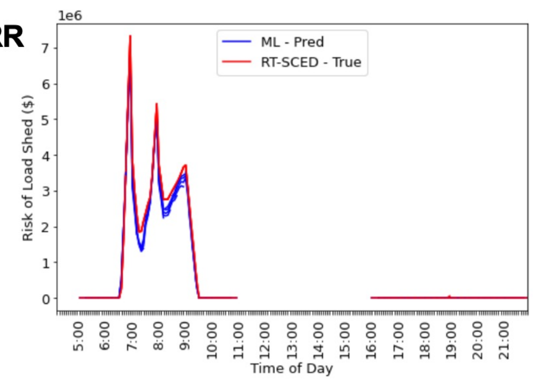
Prob of op. reserve < MRR
MAE = .02



Prob of load Shed > 0
MAE = .03



Risk of op. reserve < MRR
MAE = 4e4
Range = [0, 6.1e6]
MAE (%) = 1.9%



Risk of load shed > 0
MAE = 8e4
Range = [0, 7.3e6]
MAE (%) = 9.6%

Conclusion

- Risk-Aware Market Clearing
- Forecasting and Uncertainty Quantification
- Dimensionality Reduction
  - Asset Bundling and Support Points
- Stochastic Optimization
- Just-In-Time Machine Learning for Operations
- Real-time Risk Assessment