Deep Learning for Probabilistic Net-Load Forecasting

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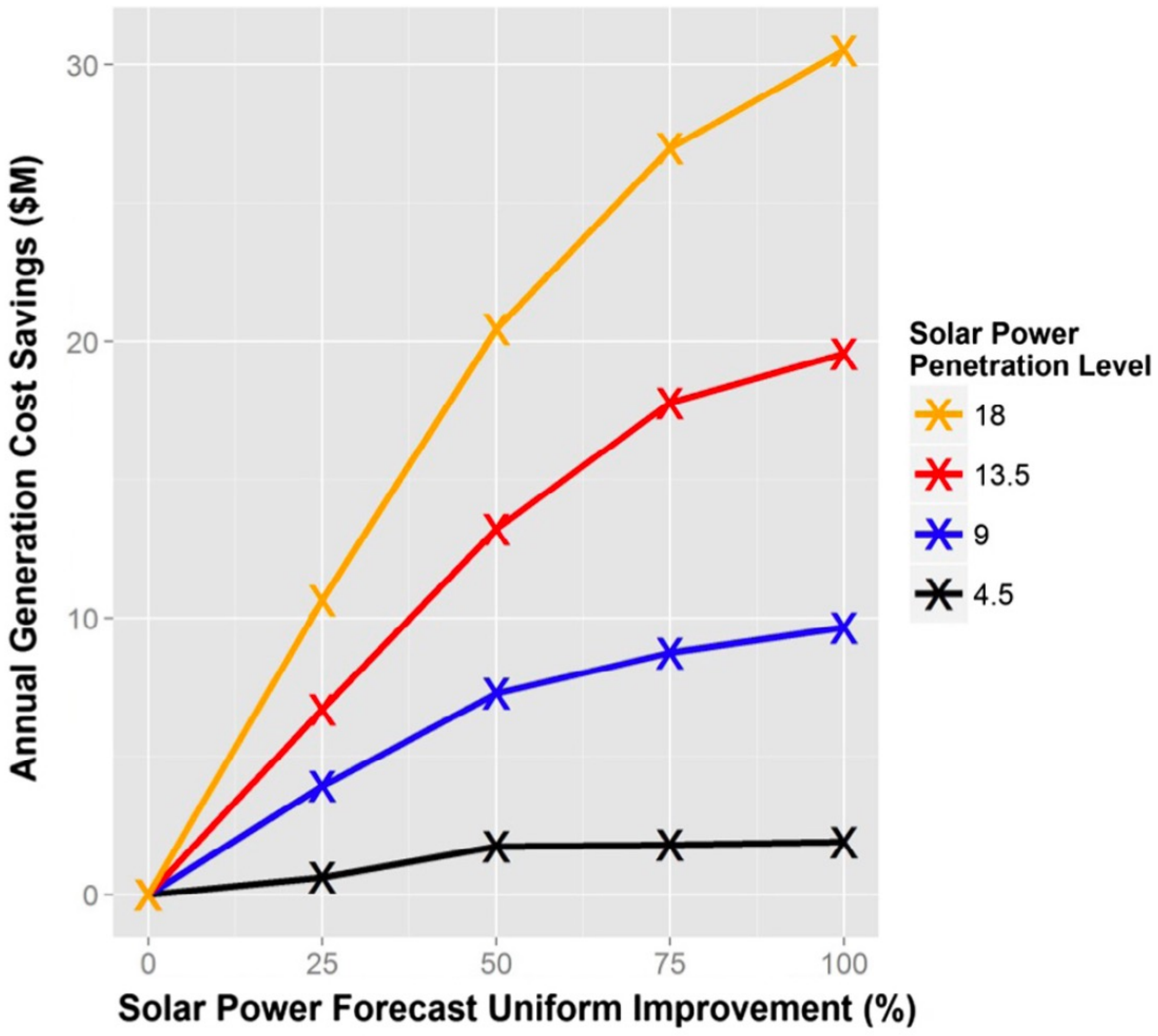
Need for Improved Net-Solar Forecast



Source: Martinez-Anido et al, Solar Energy, 2016.

Study based on ISO-New England

1) Solar forecast improvement leads to increased savings
    - Fuel costs
    - Startup and shutdown costs
    - Variable operation and management (VO&M) costs
2) Higher solar penetration leads to higher savings
3) Decreasing marginal value (savings) of improving forecast

By 2030, WECC expects a 67% increase in renewables, with 73% increase in solar and 178% in BTM solar

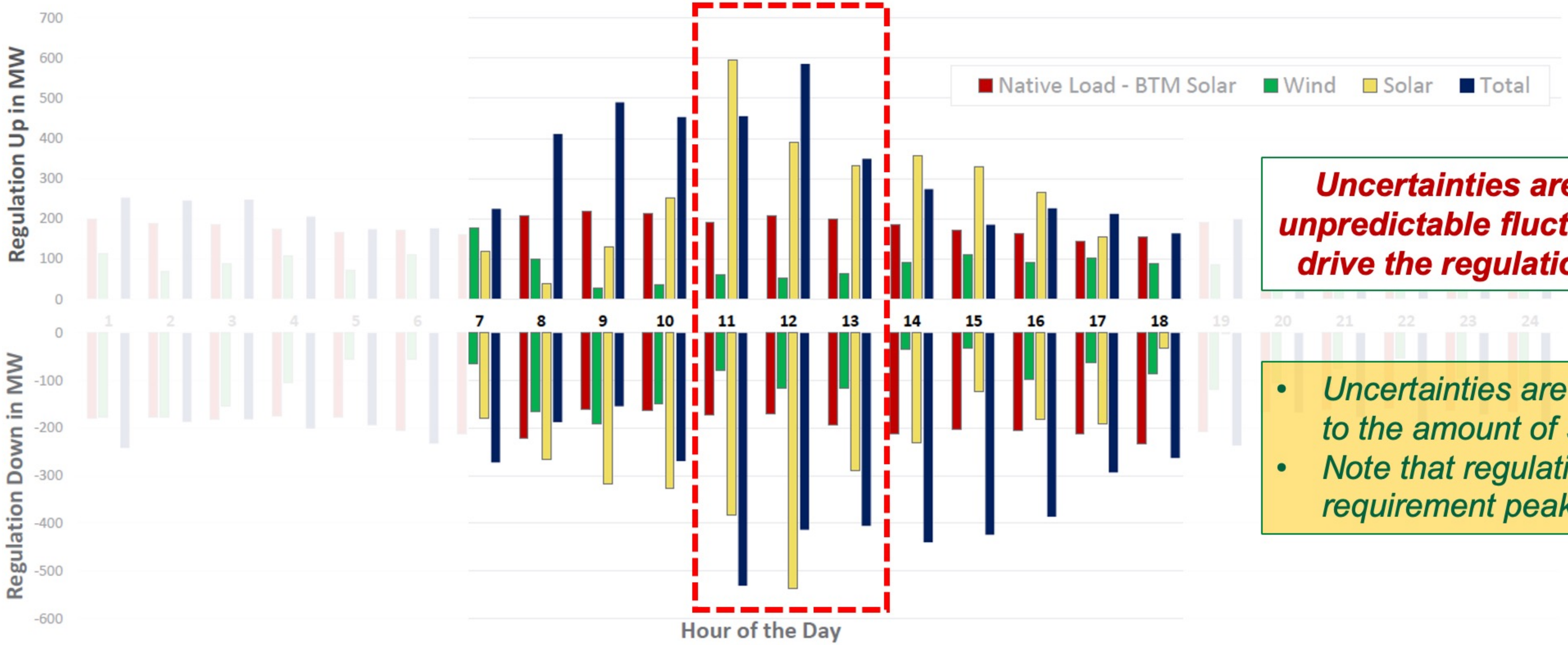
***Comparing 2019/2020 installed capacity with 2030 WECC Anchor Data Set (ADS)*

Need Methods for Improved Net-Load Forecast @Extreme Solar

Net-Load Forecast: Uncertainty vs. Variability

PNNL GRAF-Plan Tool

Tool to assess the impact of uncertainty and variability on balancing reserves



Uncertainties are real-time unpredictable fluctuations, and drive the regulation reserves

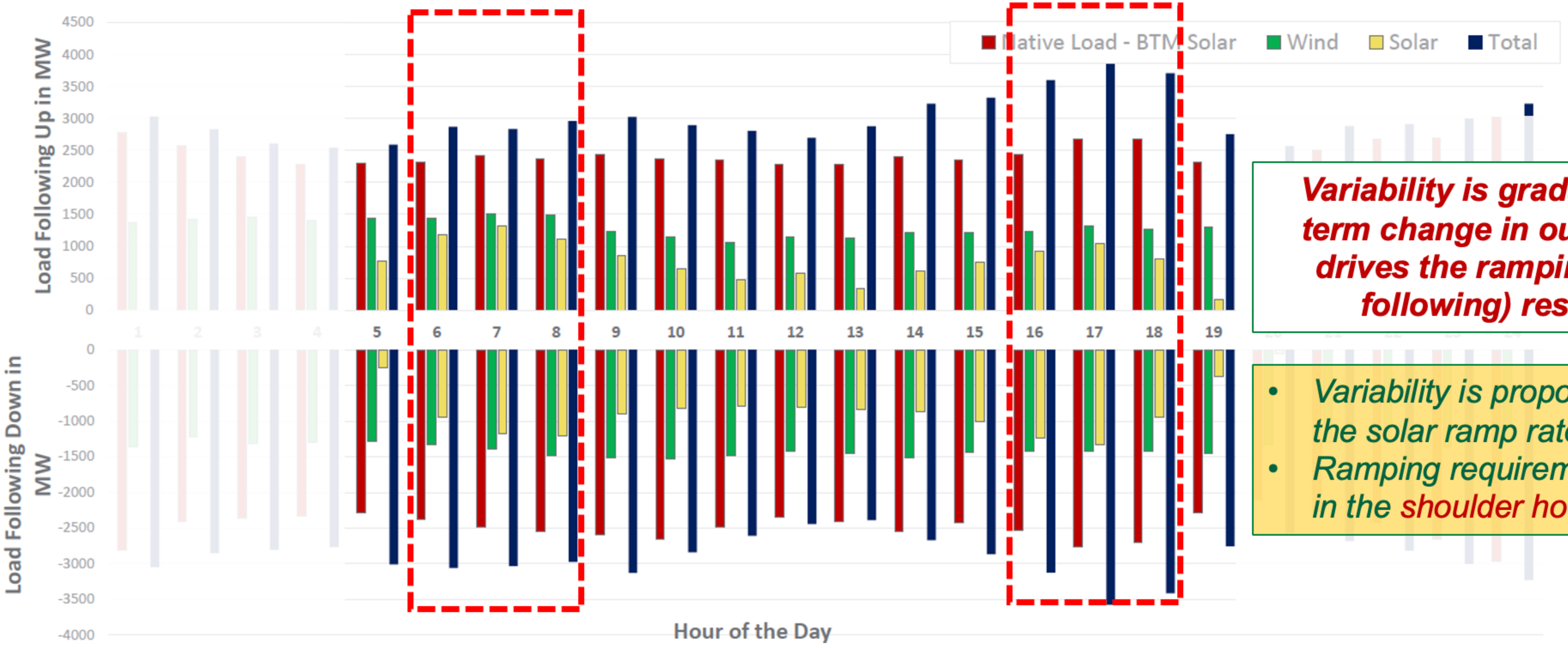
- *Uncertainties are proportional to the amount of solar output*
- *Note that regulation requirement peaks in mid-day.*

***Source**: Presentation by Nader Samaan at WECC PCM Data Work Group, 2020.*

Net-Load Forecast: Uncertainty vs. Variability

PNNL GRAF-Plan Tool

Tool to assess the impact of uncertainty and variability on balancing reserves



Variability is gradual short-term change in output, and drives the ramping (load-following) reserves

- *Variability is proportional to the solar ramp rates*
- *Ramping requirement peaks in the shoulder hours.*

***Source**: Presentation by Nader Samaan at WECC PCM Data Work Group, 2020.*

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AI/ML in Net-Load Forecast: Some Key Features

AI/ML in Net-Load Forecasting

Uncertainty

Probabilistic models that can capture real-time unpredictable fluctuations

Variability

Deep models that can capture gradual short-term change in output

Deployability

Deep models need to be fast deployed in limited data environment

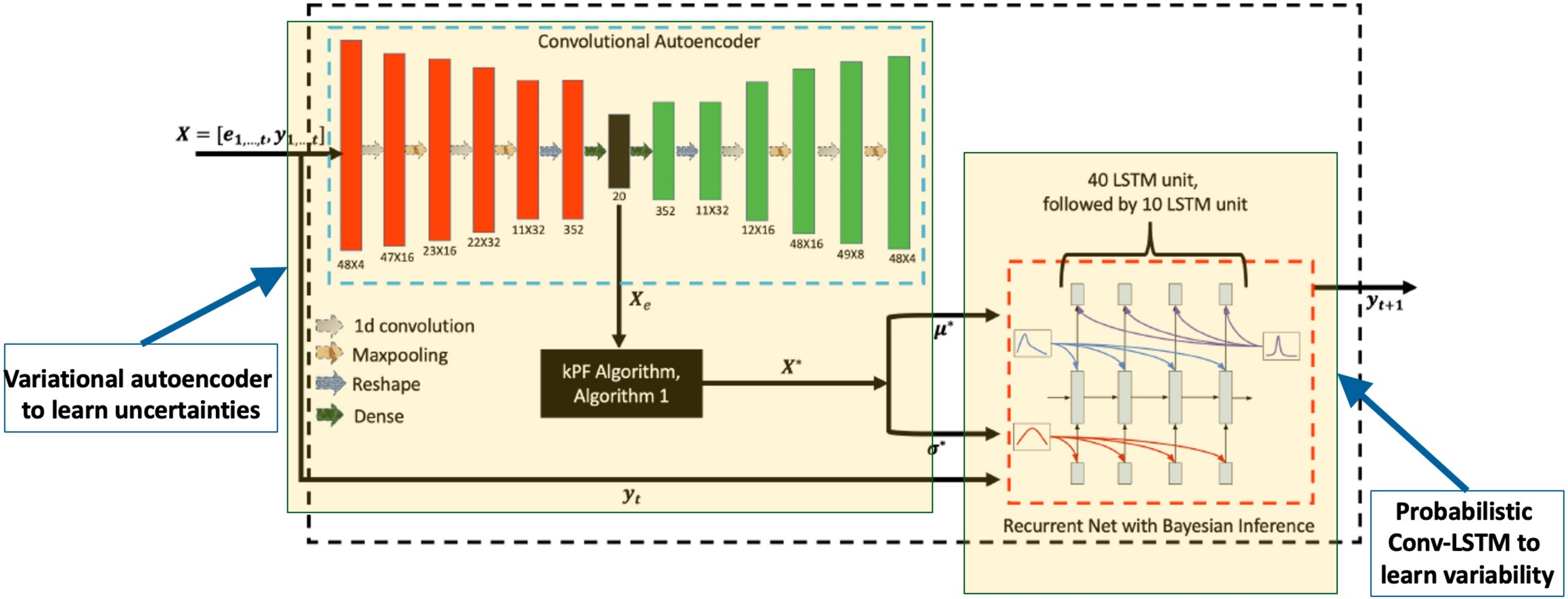
Explainability

AI/ML model outputs must be interpretable to gain trust of human operators

What We Cover Today

- **Data Availability vs. Model Complexity**
  - **Architecture 1**: Complex Model, High-Resolution (Larger) Dataset
  - Deployable AI/ML via Transfer Learning
  - **Architecture 2**: Simpler Model, Low-Resolution (Smaller) Dataset
- **Explainability of AI/ML Models**
  - Trust-Augmented AI/ML via Interactive Visual Analytics

Architecture 1: kPF-AE-LSTM (a VRNN model)

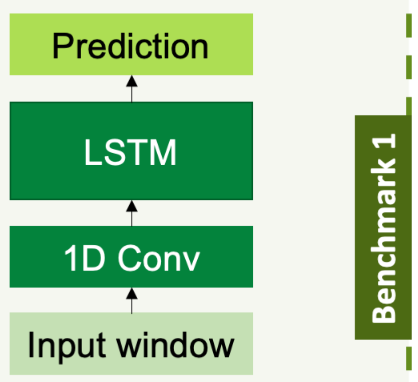


A Variational Recurrent Neural Network (VRNN) model that combines an Autoencoder and a Long-Short-Term-Memory (LSTM) network with a kPF Algorithm (kPF-AE-LSTM)

Architecture 1: Comparison with Benchmark

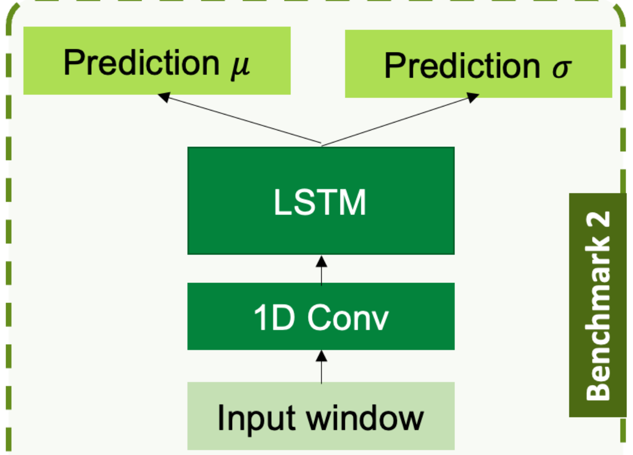
Model	Training Loss	Train time /epoch (s)	MAE (kW)	Norm MAE (%)	MAPE (%)	APE IQR (%)	PBB (%)	CRPS
PCLSTM	CRPS	4.1	9.1	10.7	11.2	7.6	74.57	0.25
PCLSTM	NegLL	4	11.2	13.1	13.3	6.9	73.23	0.39
CLSTM	MAE	4.1	10.8	12.6	13.4	13.3	NA	NA
VRNN	Recon+NegLL+Pred error	7.8	5.6	6.5	6.5	4.1	93.23	0.13
VRNN	Sequential training	4	5.6	6.4	6.6	4.1	93.43	0.12

- The proposed model outperforms the benchmarks by ~30% in forecast accuracy
- While still achieving the best-in-class training efficiency (~4s)



Convolution-LSTM (CLSTM)

- *A regular LSTM, with a 1-dimensional Convolution layer added to the input*

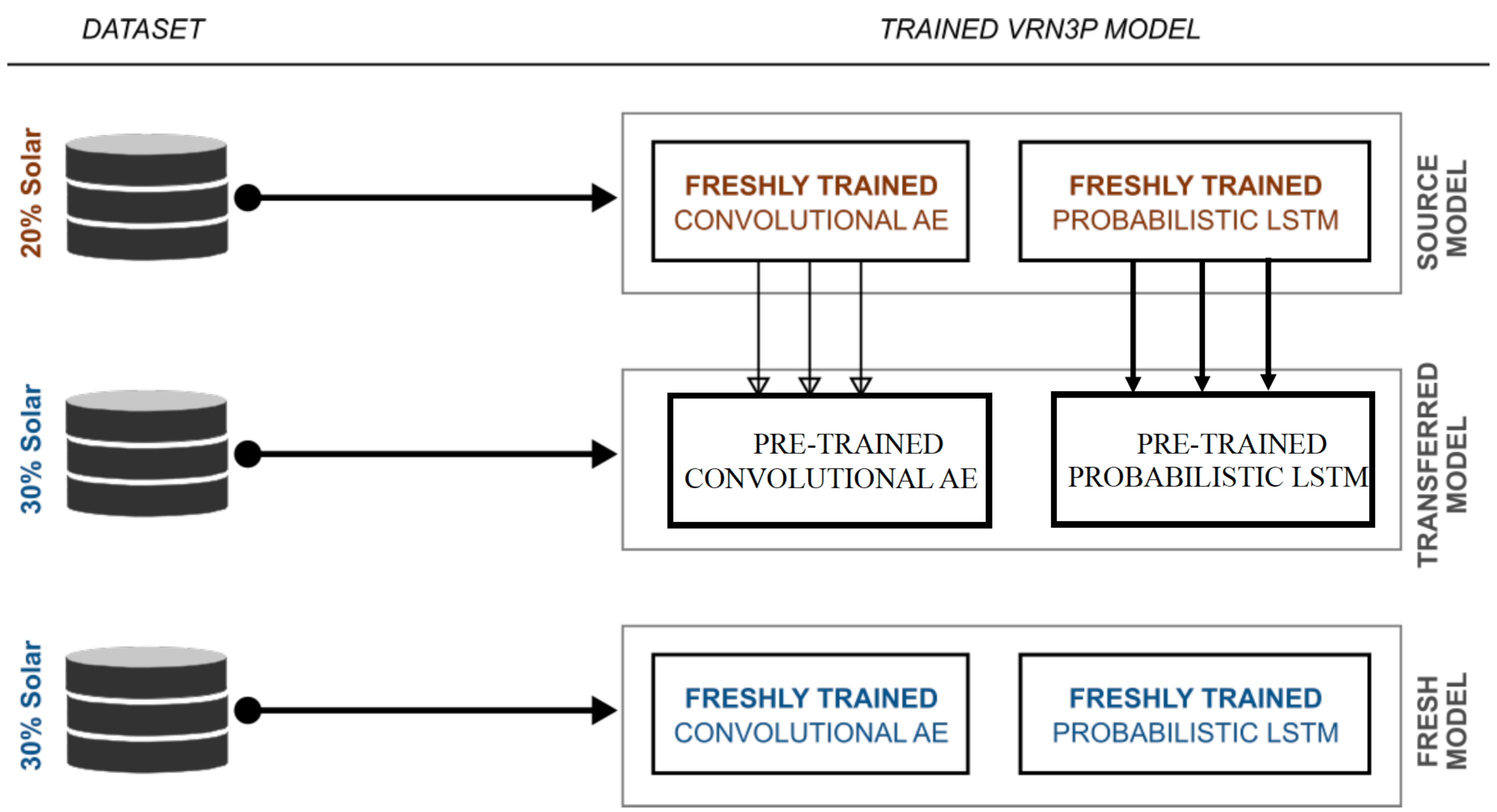


Probabilistic CLSTM (PCLSTM)

- *A CLSTM that predicts the mean and variance of the forecast distribution*

CRPS = Continuous Ranked Probability Score,
NegLL = Negative Log-Likelihood, MAE = Mean Absolute Error,
PBB = Probability between Bounds, IQR = Inter-Quartile Range

Deployable AI/ML via Transfer Learning



Case	Data Size (# samples)	Hourly MAPE	Training Time (sec/epoch)
30% BTM (Transferred)	8,800	2.15%	0.56
30% BTM (Fresh Trained)	35,040	1.57%	3.35

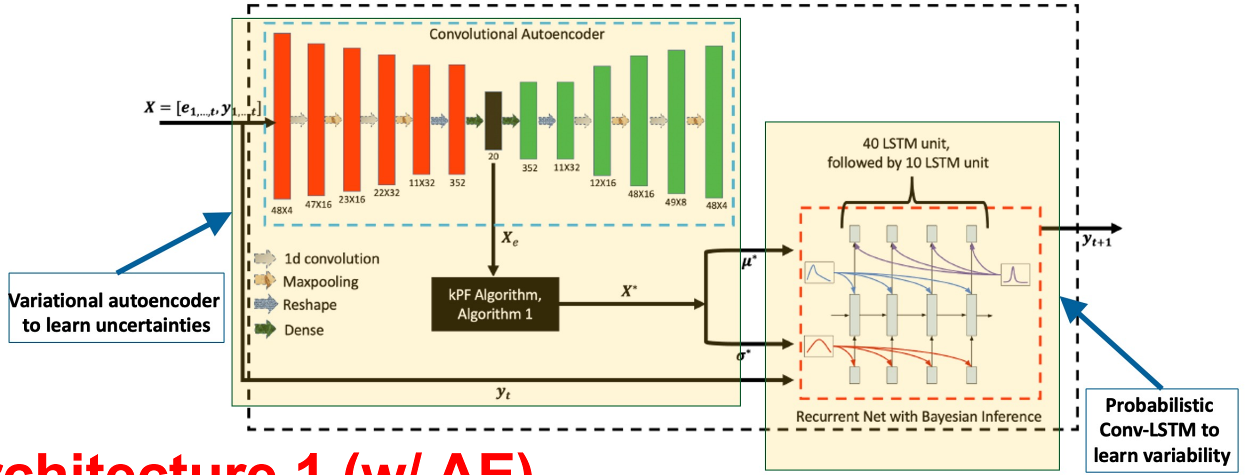
Transferring model trained on 20% solar case to 30% solar case

Only 25% of data used in training transferred model

Acceptable forecast accuracy with 6x speed-up in training time

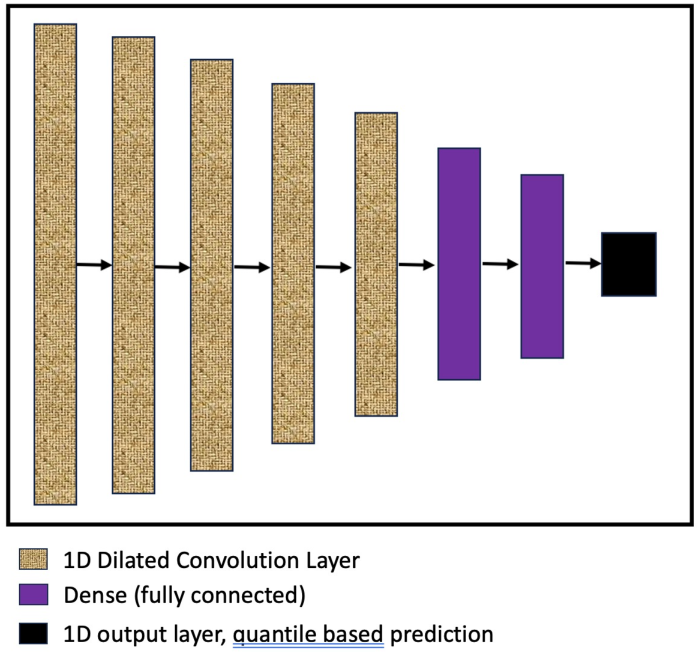
Seems to work only within the same (similar) weather zone

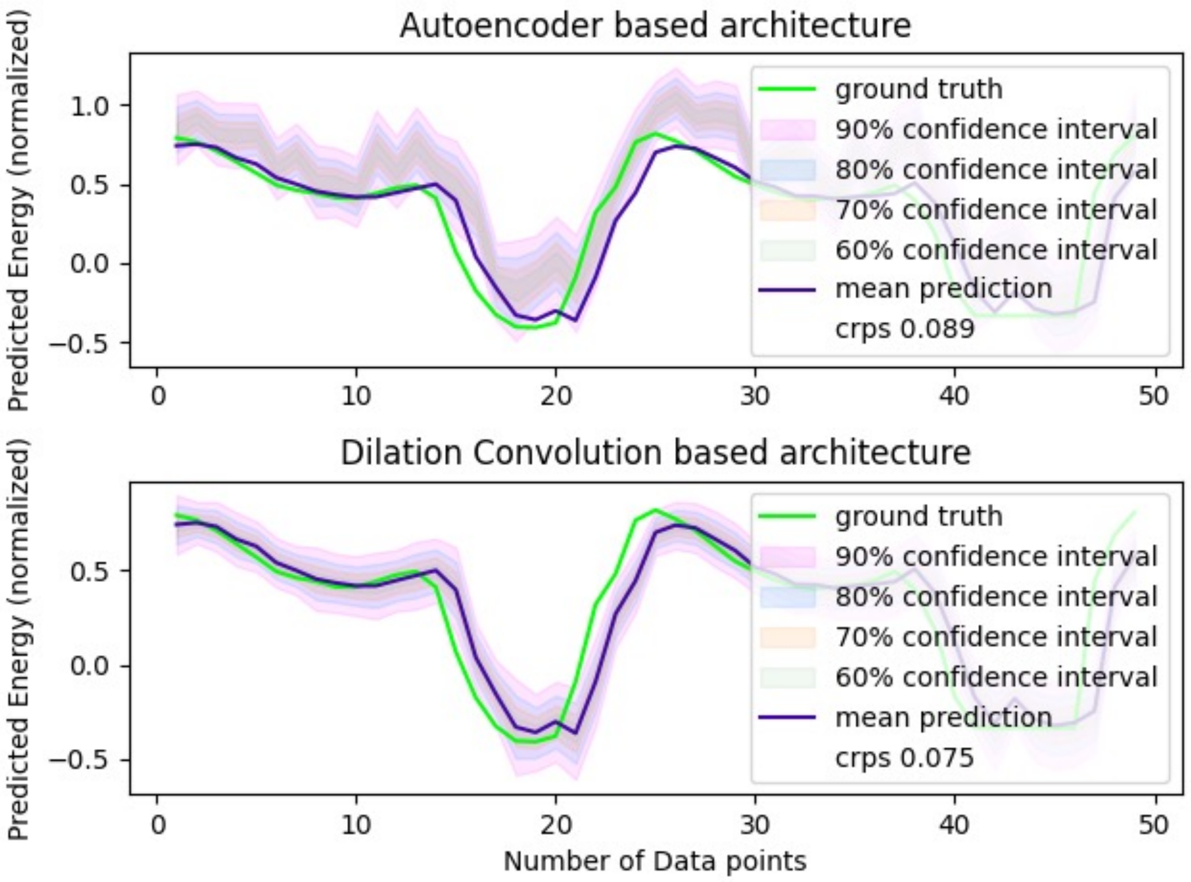
Architecture 2: Simpler Model, Low-Res Data



Architecture 1 (w/ AE)

Architecture 2 (w/o AE)





Simpler model (w/o AE) outperforms AE-based model by achieving lower CRPS in low-resolution data environment

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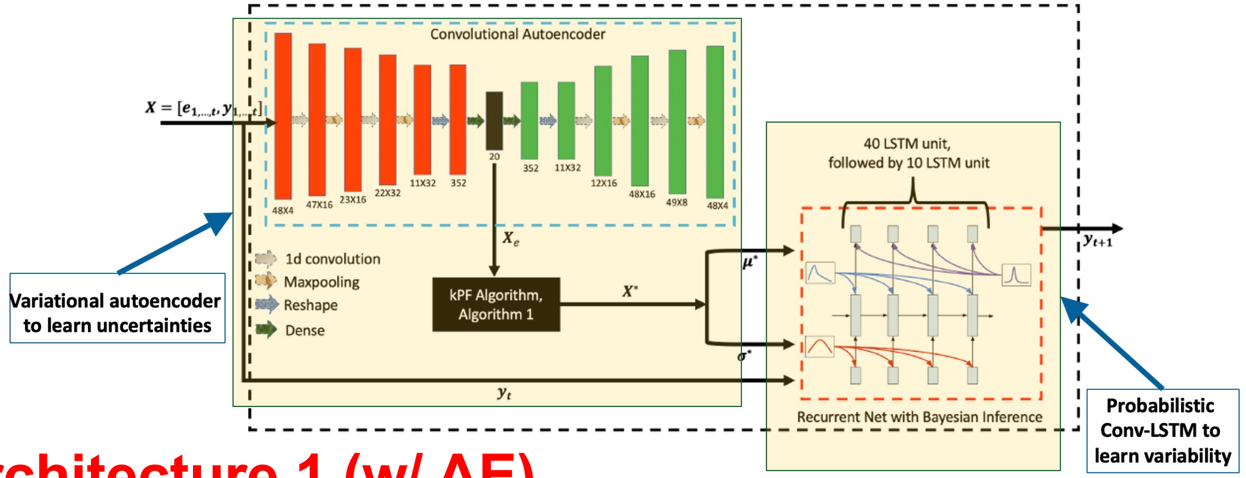

Architecture 1 (w/ AE)

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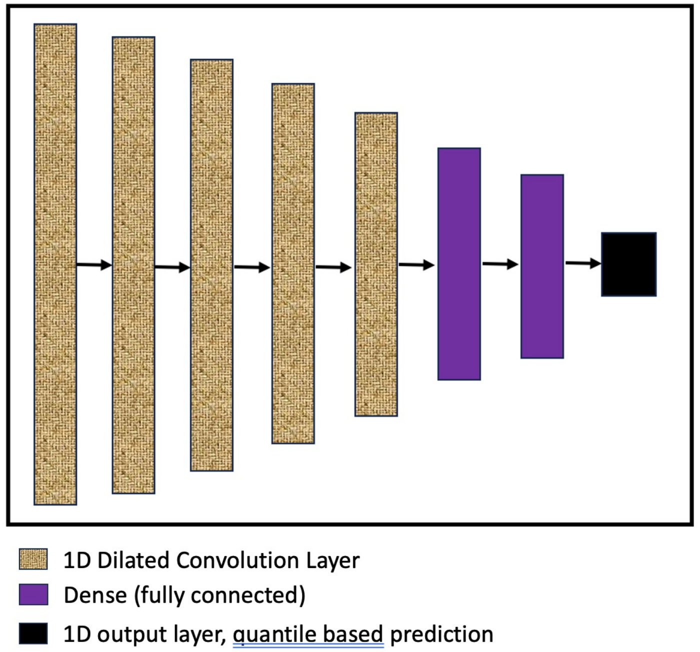

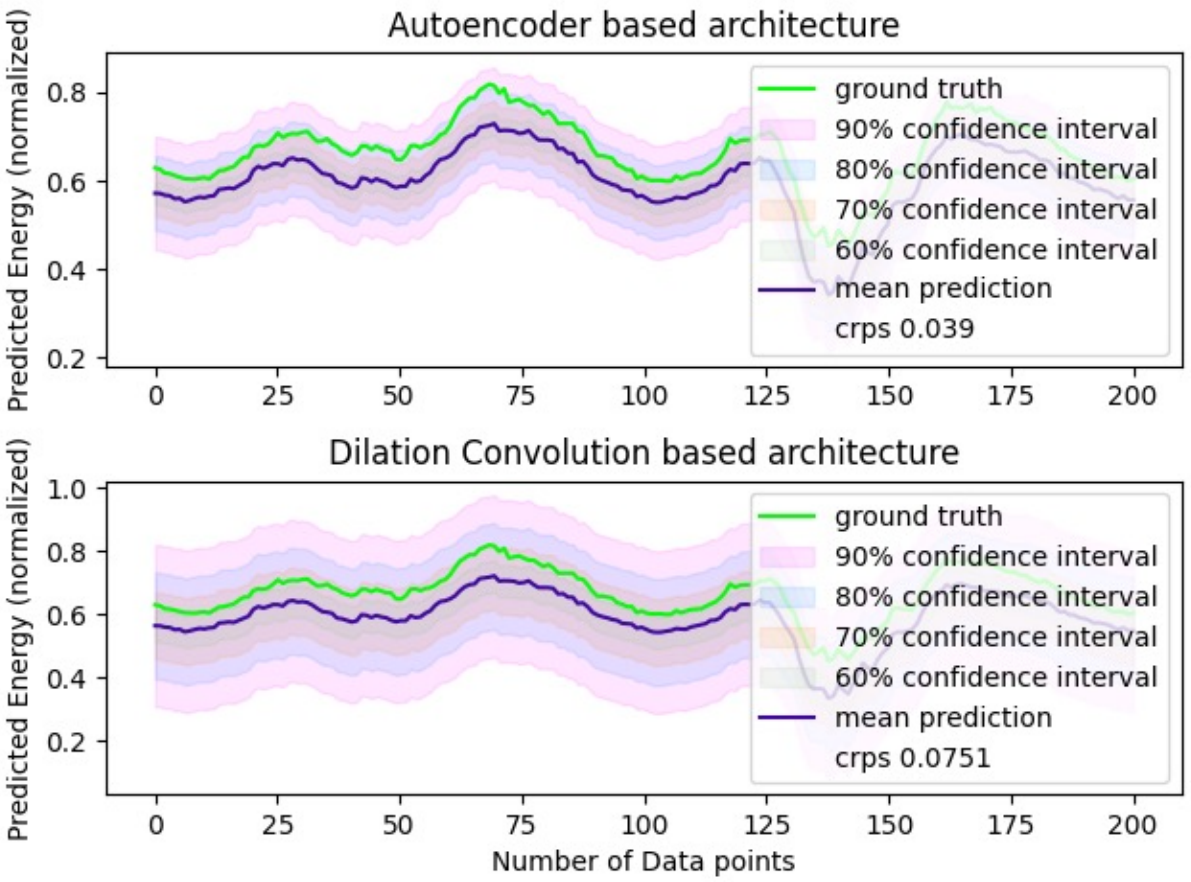

In high-resolution data, simpler model (w/o AE) expectedly does worse by achieving higher CRPS than AE-based model

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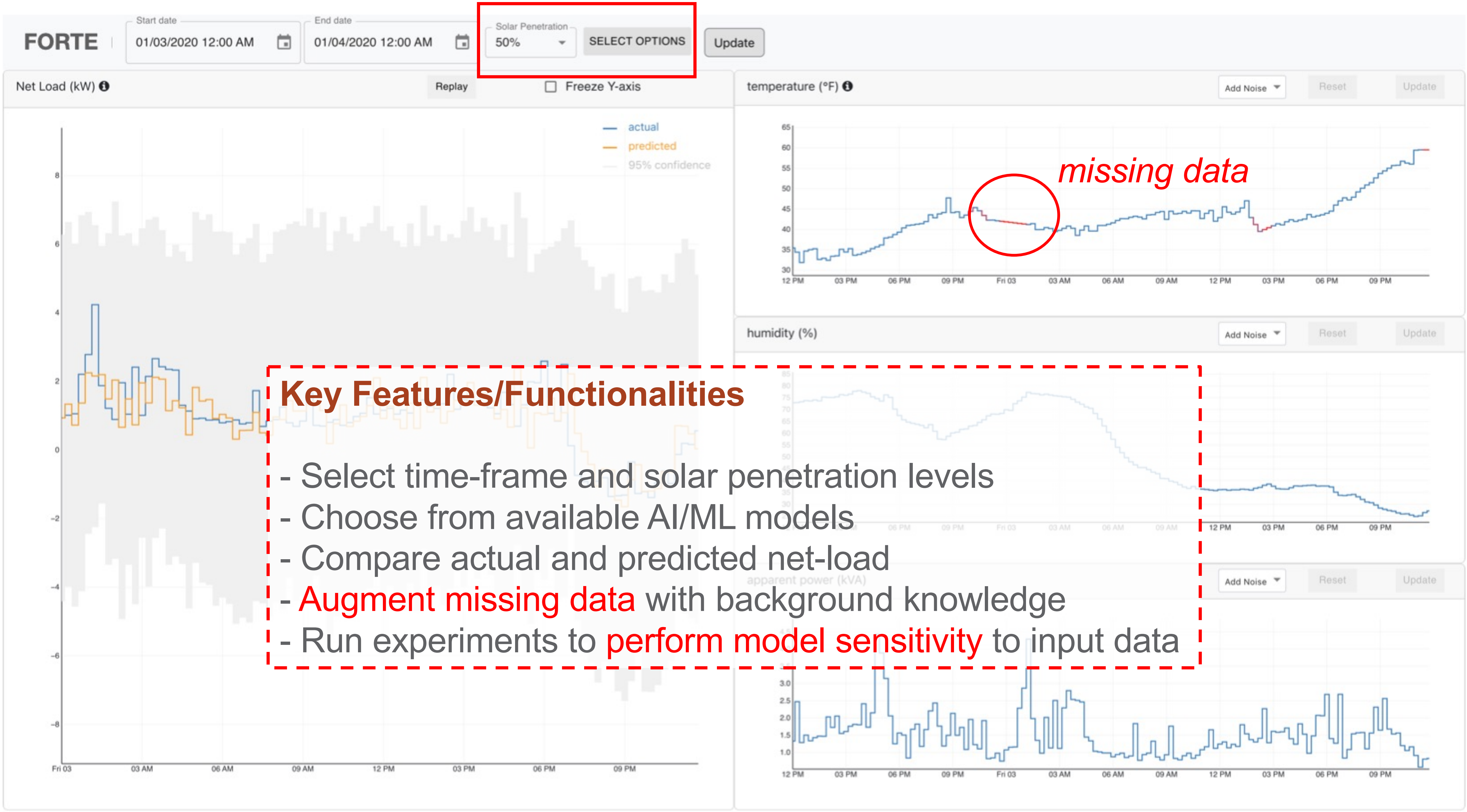
Forte: Interactive Tool for Net-Load Forecasting

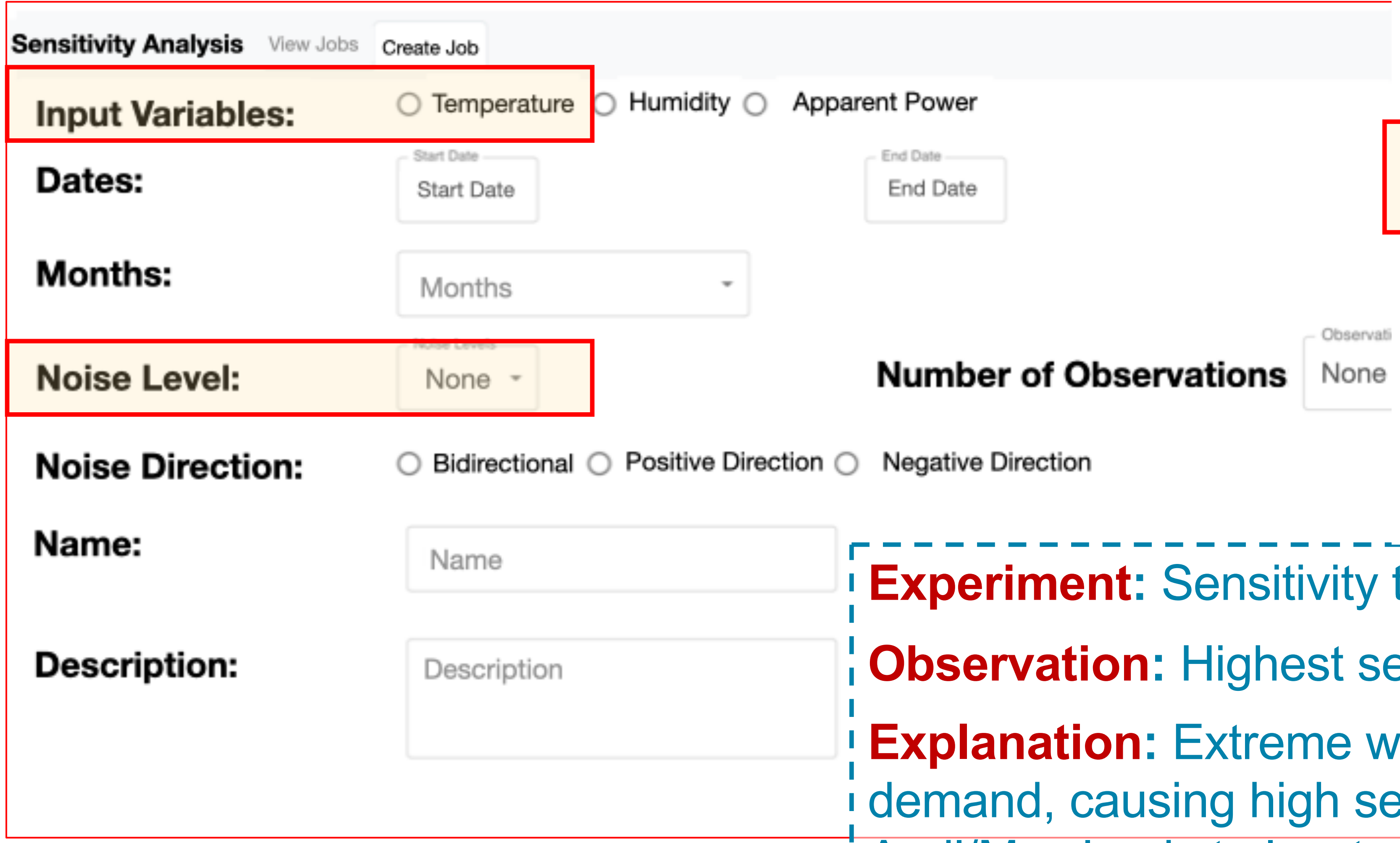


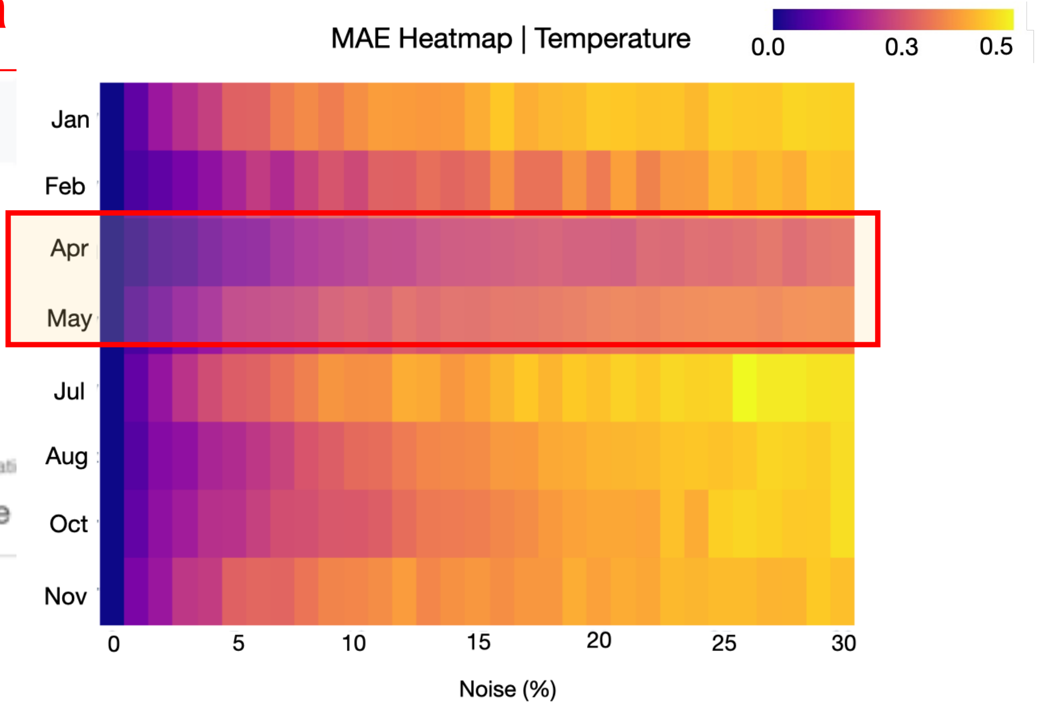
Key Features/Functionalities

- Select time-frame and solar penetration levels
- Choose from available AI/ML models
- Compare actual and predicted net-load
- Augment missing data with background knowledge
- Run experiments to perform model sensitivity to input data

Forte: Interactive Tool for Net-Load Forecasting

Run experiments to perform model sensitivity to input data





Experiment: Sensitivity to temperature

Observation: Highest sensitivity in Jan/Jul, lowest in April/May

Explanation: Extreme weather in Jan and Jul drives energy demand, causing high sensitivity. In contrast, milder weather in April/May leads to low temperature sensitivity of net-load

More Information

- Forte Interface is available on GitHub: https://github.com/pnnl/Forte
- Publications:
  - Sen, Chakraborty, Kundu, et al. "KPF-AE-LSTM: A Deep Probabilistic Model for Net-Load Forecasting in High Solar Scenarios." arXiv preprint arXiv:2203.04401 (2022).
  - Bhattacharjee, Dasgupta, Kundu, Chakraborty. “Forte: An Interactive Visual Analytic Tool for Trust-Augmented Net-Load Forecasting”, submitted to ISGT (2024).

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Thank you

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