Hybrid Renewable Energy Forecasting and Trading Competition 2024

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Results of the Hybrid Energy Forecasting and Trading Competition 2024

International Symposium on Forecasting

Monday 1 July 2024

WORLD CHANGING GLASGOW

Dr Jethro Browell
Senior Lecturer
School of Mathematics and Statistics
University of Glasgow
jethro.browell@glasgow.ac.uk

THE TIMES THE SUNDAY TIMES GOOD UNIVERSITY GUIDE 2024 SCOTTISH UNIVERSITY OF THE YEAR

Agenda

- Overview
- Analysis
- Winning team presentations:
  - Chuanqing Pu, *GEB*
  - Gergo Barta, *UI BUD*
  - Tarun Raj, *Rnt*
  - Jakob Huss, *SVK*

HEFTcom Organising Committee: Jethro Browell (Chair, University of Glasgow), Sebastian Haglund & Henrik Kälvegren (rebase.energy), Dennis van der Meer (Ørsted), Ricardo Bessa (INESC TEC), Yi Wang (University of Hong Kong)

Thanks also to: Edoardo, Alex, Chris and David (Ørsted), Melissa and Alex (IEEE DataPort), Pierre Pinson (Imperial College), Klimis Stylpnopoulos (University of Glasgow)

Background and motivation

Background

- Forecasting is a key capability for net-zero energy systems
- Trading is the primary mechanism that matches supply and demand
- Crisis in academic publishing!

Motivation

- (Re-) establish best-in-class methods
- Enable use of all data available to participants
- Explore relationships between forecasting and decision-making
- Promote energy forecasting and decision-making problems


Set-up
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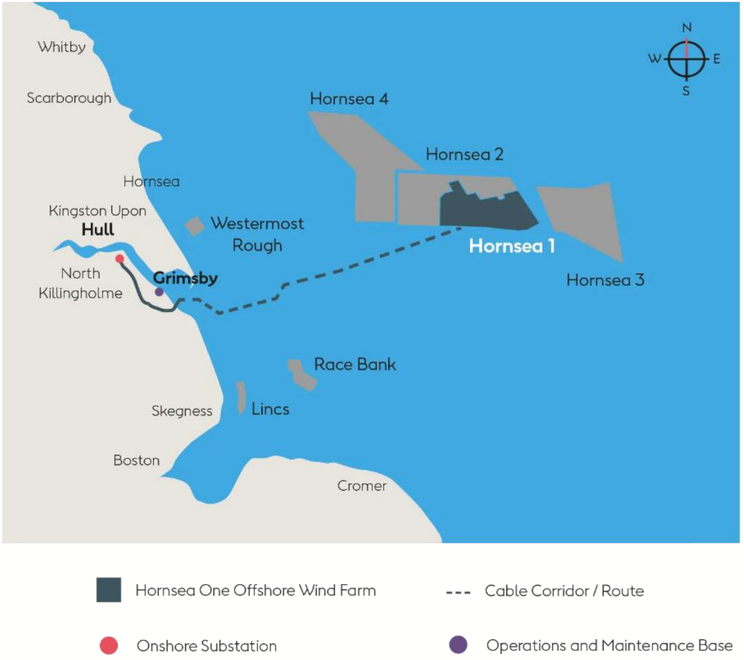
Hybrid Portfolio of Wind and Solar

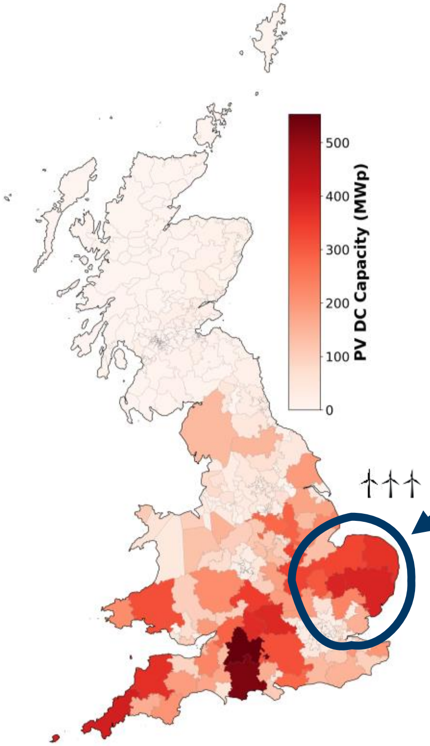
Hornsea 1 Wind Farm

- 1.2GW capacity
- 174 wind turbines
- 407km^2 in the North Sea
- 900km of cable



Source: https://orsted.co.uk/energy-solutions/offshore-wind/our-wind-farms/hornsea1

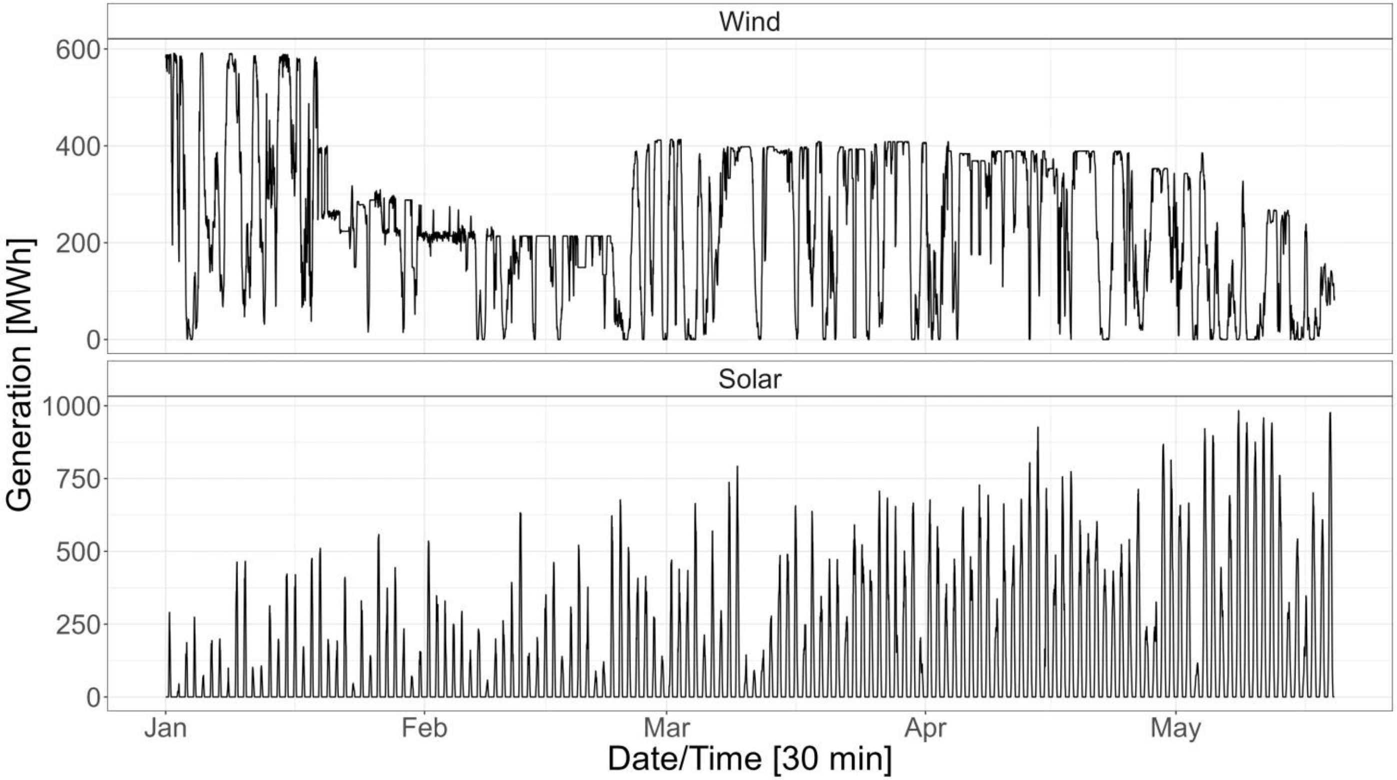
Hybrid Portfolio of Wind and Solar



Solar portfolio

- Approximately 2.6GW capacity
- Over 100,000 installations
- Range from domestic (less than 4kW) to 50MW commercial farms

Hybrid Portfolio of Wind and Solar



Hybrid Portfolio of Wind and Solar

Forecasting track

- Target: total production from the hybrid portfolio
- Forecasts: quantiles 10%, 20%,...,90% for each half-hour period of the day-ahead
- Score: Pinball Loss

Trading track

- Based on Great Britain’s wholesale electricity market
- Submit: day-ahead market bids for each half-hour of the day-ahead
- Score: revenue after imbalance

Real-time competition!
Submission via API by 09:20 UTC for each half-hour of the day-ahead
Testing period followed by daily submissions for 3 months

Trading task explainer

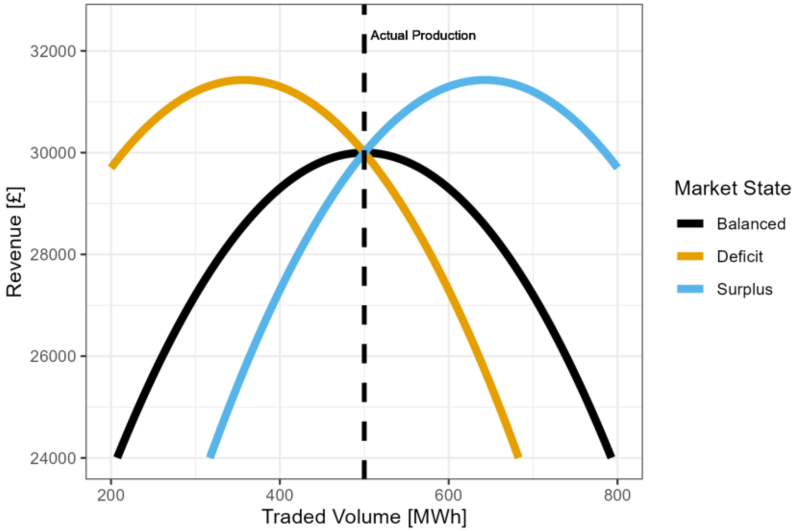
The electricity market incentivises participants to self-balance…

1. Energy is traded ahead of time
2. The difference between traded and actual generation is settled at the *imbalance price*

Imbalance price:

- Punitive if the participant is exacerbating overall the market surplus/deficit
- Favourable if the participant is alleviating the overall market surplus/deficit, up to a point…
- Price-maker effect modelled based on historic elasticity

Example:
Day-ahead price = £60/MWh
Imbalance price (market deficit) = £80/MWh
Imbalance price (market surplus) = £40/MWh
Actual production: 500MWh



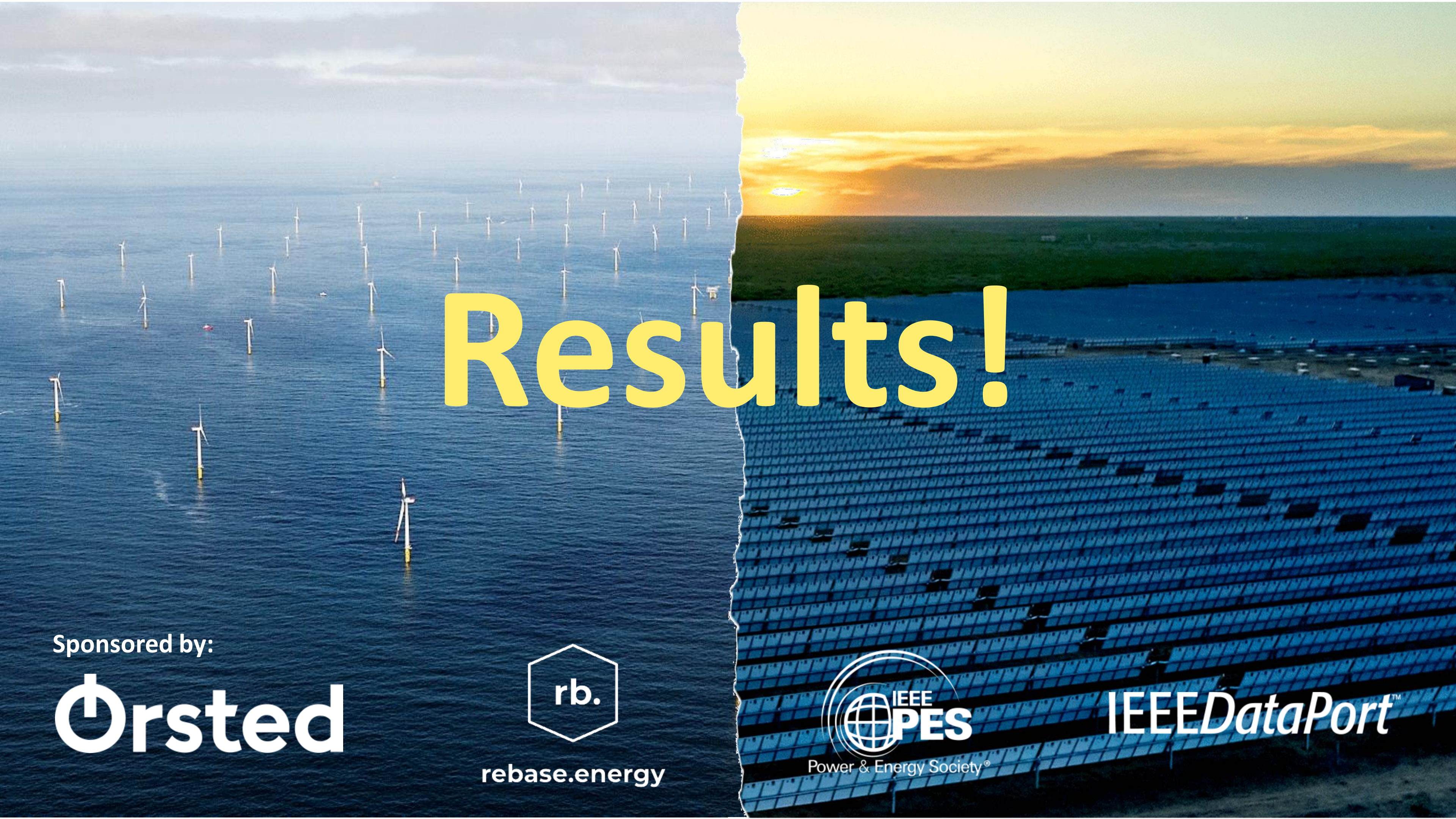
Competition platform

Static

- Documentation
- Historic weather forecasts
  - Two providers
  - Gridded data
- Historic energy data
  - Generation from wind and solar plants
  - Prices
- *Getting Started Guide*

Live!

- Slack to interact with organisers and other participants
- API to retrieve latest data, including most recent weather forecast
- API submission of forecasts and trades
  - 09:20 UTC deadline
  - Testing period prior to start of competition
- Rolling leaderboard


Results!
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Results: Combined Track

Combined Track Rank	Team	Pinball [MWh]	Revenue [£m]	Student Team?
1	SVK	22.18	88.88	
2	Rnt	24.64	88.29	
3	UI BUD	23.18	88.07	
4	GEB	25.16	88.18	Student Team
5	BridgeForCast	25.34	87.67	
6	Sukantabasu	27.04	87.83	
7	Stochastic Parrots	27.50	87.53	
8	EnergiWise	27.65	87.43	
9	Ihubex	29.22	87.64	Student Team
10	LSEG Power Team	25.74	85.71	

University of Glasgow

Participants

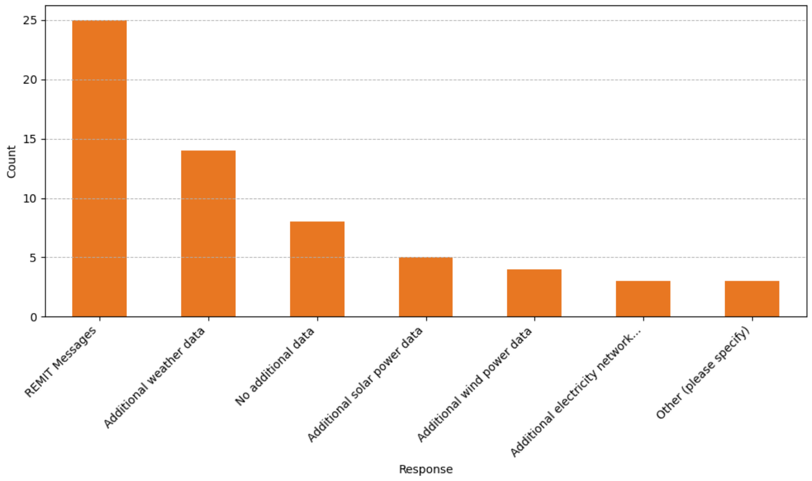
Completion of HEFTcom 2024:

- >170 teams registered
- 66 teams actively participated
- 24 teams completed
- 5 of which are student teams

Team summary:

- 1 to 4 members was typical
- Mainly European; Asia, Africa and North America represented
- 75% automated their solution requiting only occasional intervention
- Around 1/3 teams used cloud computing

Preliminary Analysis: Forecasting Data



Several teams used additional NWP:

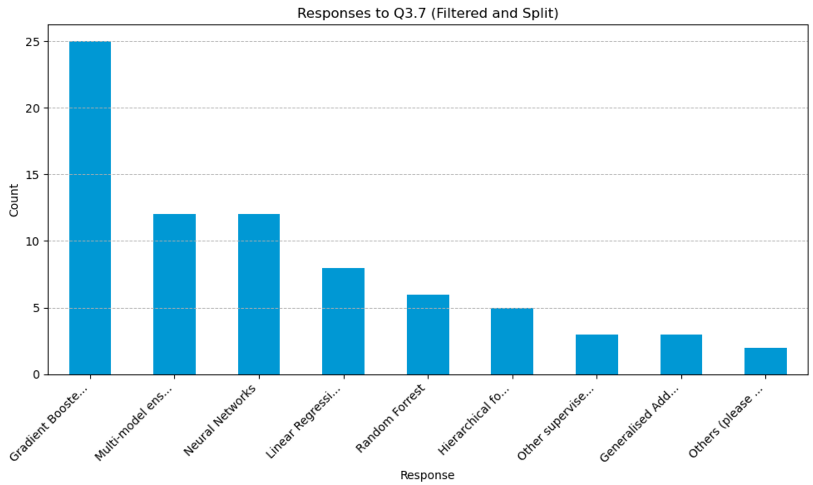
- Ensemble NWP
- One top-5 team used an in-house AI weather forecast
- Two of the top 5 used only HEFTcom data

REMIT was widely used

Preliminary Analysis: Forecasting Methods

Top methods:

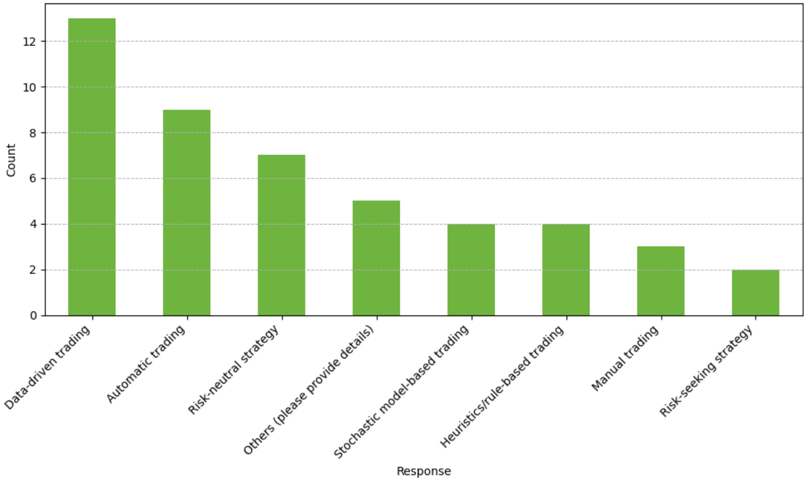
- Gradient Boosted Trees
  - CatBoost, LightGBM, XGBoost all featured
- Multi-model ensembles
- *Consistent with past competitions*



Details make the difference:

- Quantile aggregation
- Feature engineering

Preliminary Analysis: Trading



A wide variety of trading strategies, even among top performing teams:

- Optimal bid calculated from energy and price forecasts
- Directly predict optimal bid
- Trade deterministic forecast

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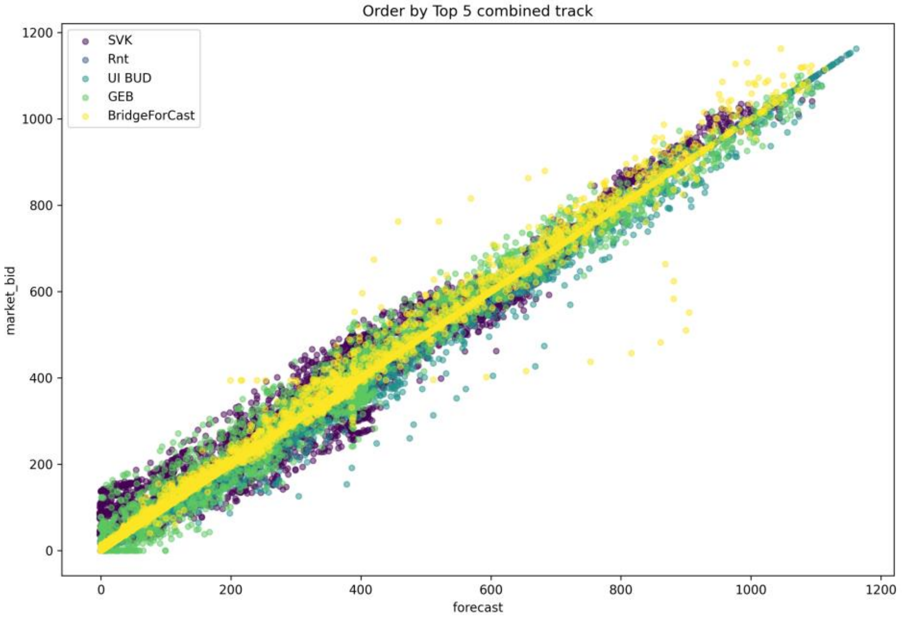
Congratulations to the winners!

And a big thank you to all participants

Dr. Dennis van der Meer

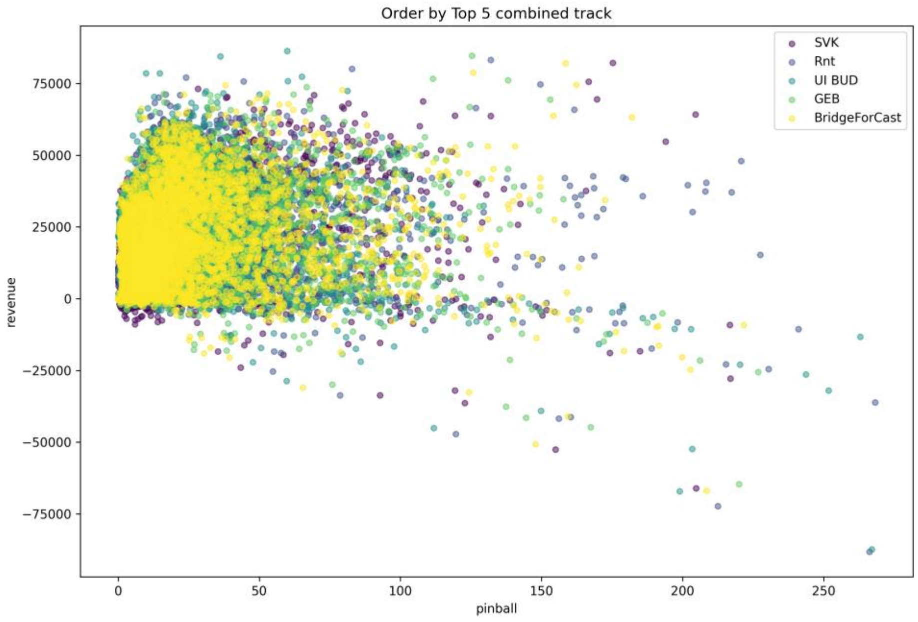
Analysis: Forecasts (p50) versus bids of top 5 from the combined track

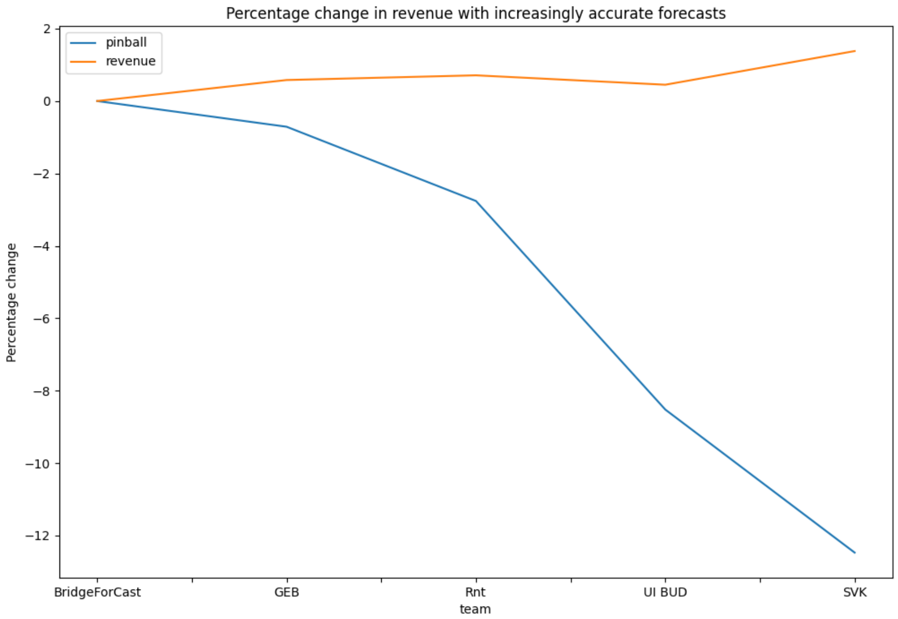


Revenue (M GBP)

Team	Bid as forecast	Strategic bid
SVK	88.29	88.88
Rnt	88.10	88.29
UI BUD	88.39	88.07
GEB	87.68	88.18
BridgeForCast	86.23	87.67

Analysis: Forecast value





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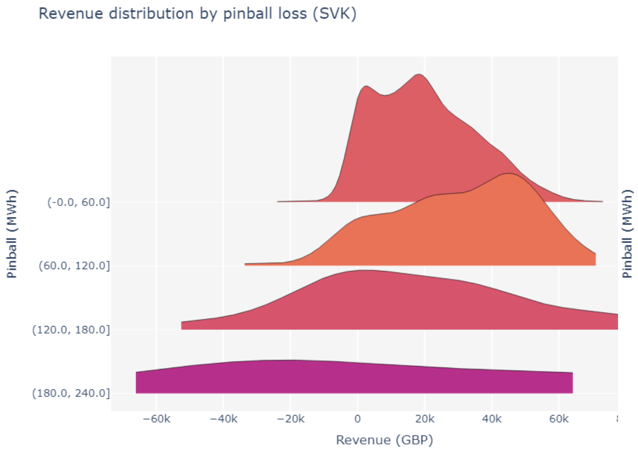
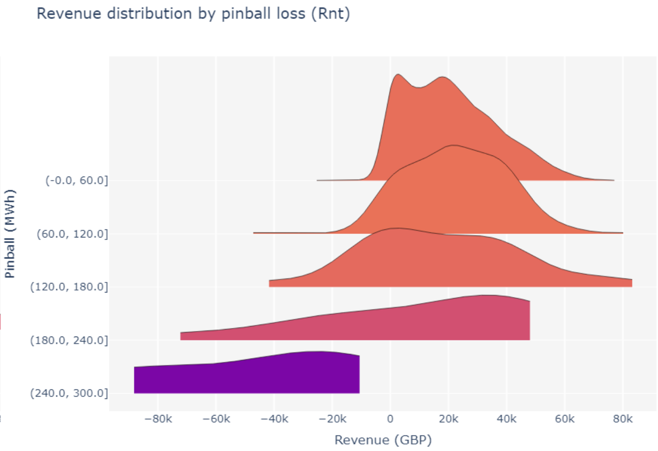
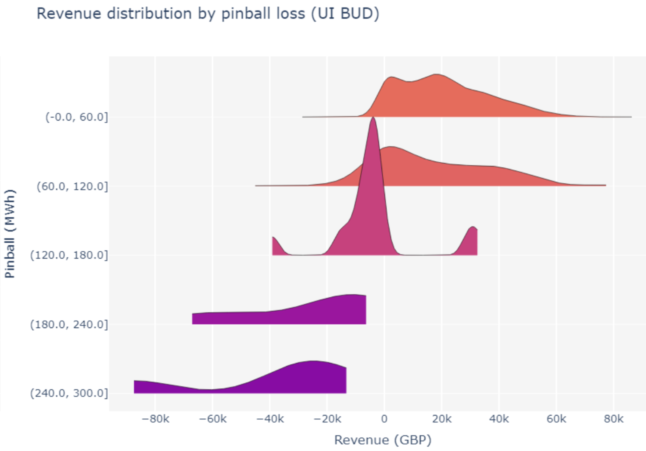
Analysis: Revenue distribution by pinball loss







- Low pinball leads to consistently higher revenues
- Neither Rnt nor UI BUD managed to generate positive revenue when pinball > 240 MWh.
- Even (moderately) high pinball can result in high revenues

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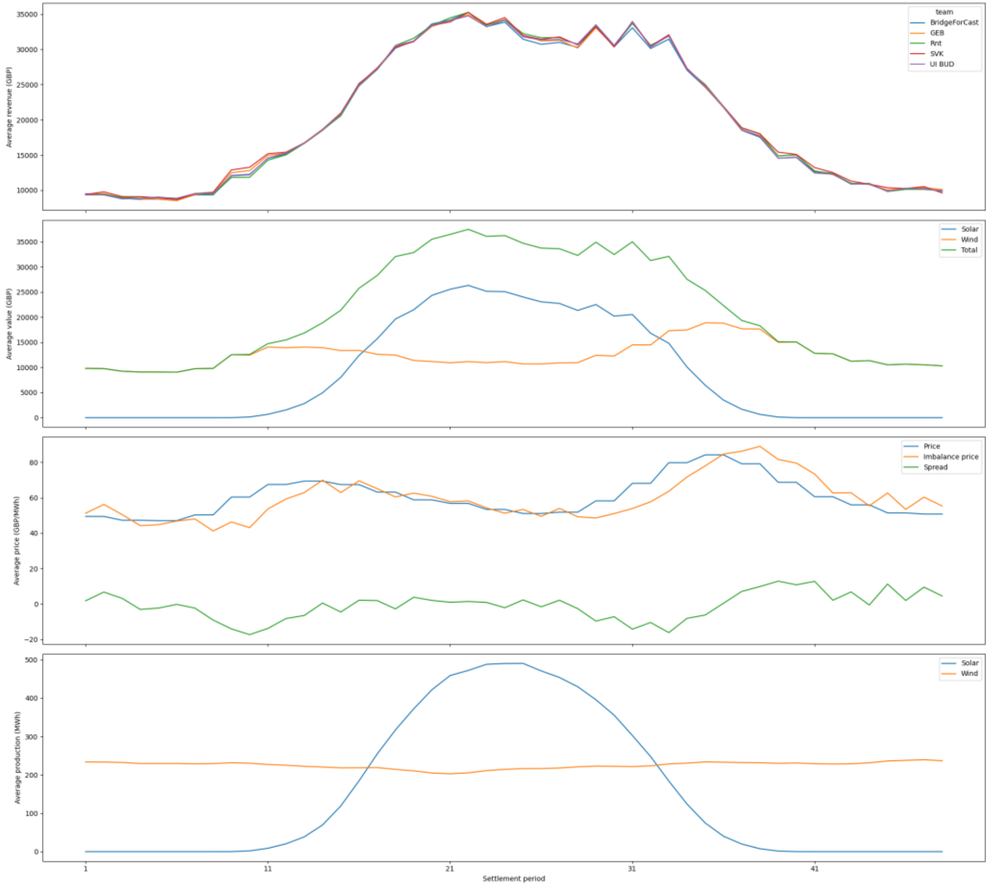
Revenues, value, prices, and power aggregated by period



- Highest average revenues achieved during the day for all participants
- More power production and less penalization when the forecast is off (spread close to zero)
- Team SVK seem to benefit more than the other teams from the price spread in the early morning and early evening

What’s next…

- Competition data is open, can you beat the top teams?
- Rolling submission and leaderboard is continuing
  - 🌐 rebase.energy/challenges/
- An article describing the competition is in preparation
- **Time to hear from the winners!**

Decoupled Probabilistic Forecasting for Hybrid Power Plants and Stochastic Programming-Based Value-Oriented Trading Strategy

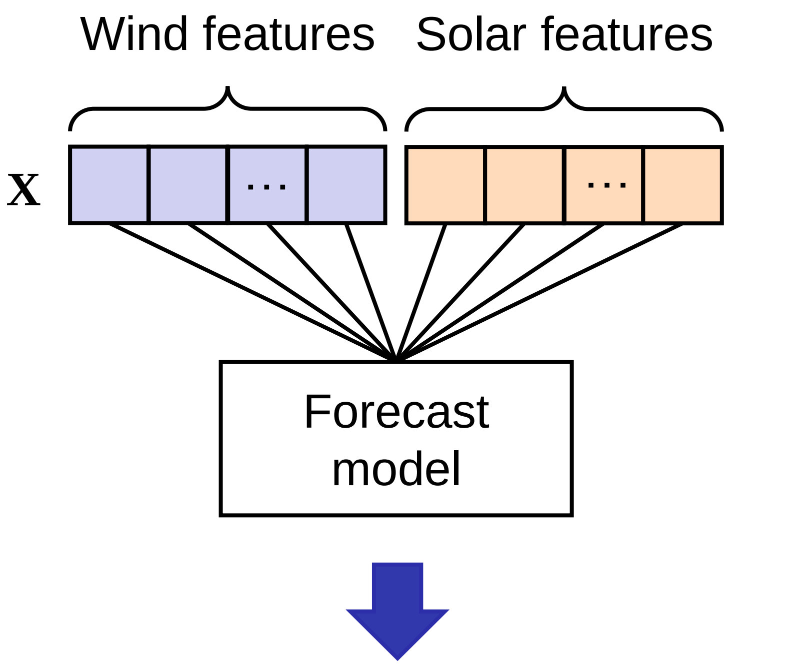
Chuanqing Pu

College of Smart Energy, Shanghai Jiao Tong University

2024/7/8

Forecasting Track—Main Idea

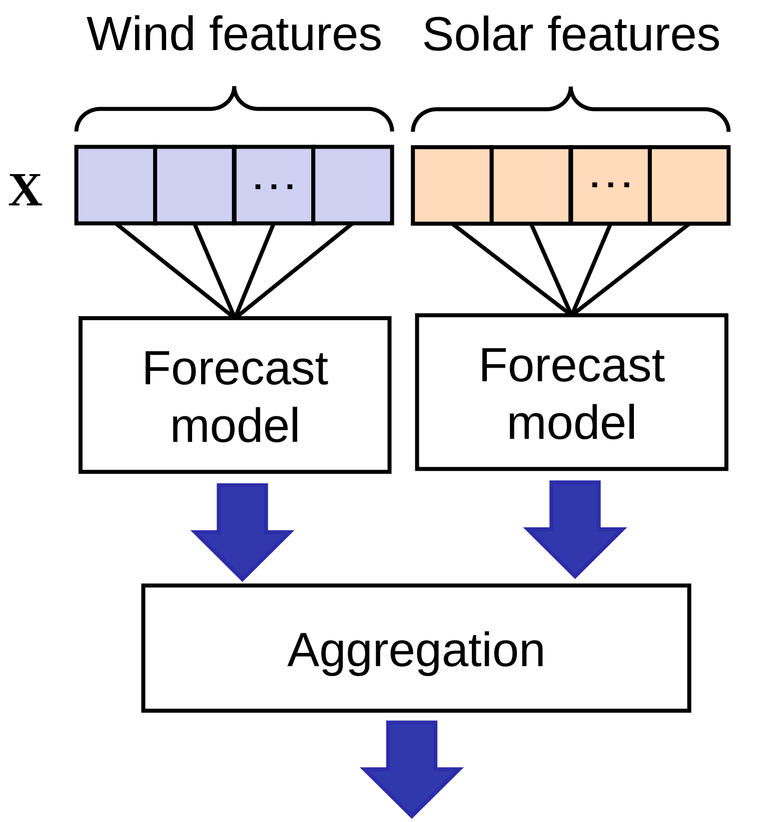
1. Directly forecast the total generation



Quantile forecast of total generation z

$$Q_{10\%}\left(z \mid \mathbf{X}\right),\ldots,Q_{90\%}\left(z \mid \mathbf{X}\right)$$

2. Decoupled forecast and aggregation



Quantile forecast of total generation z

$$Q_{10\%}\left(z \mid \mathbf{X}\right),\ldots,Q_{90\%}\left(z \mid \mathbf{X}\right)$$

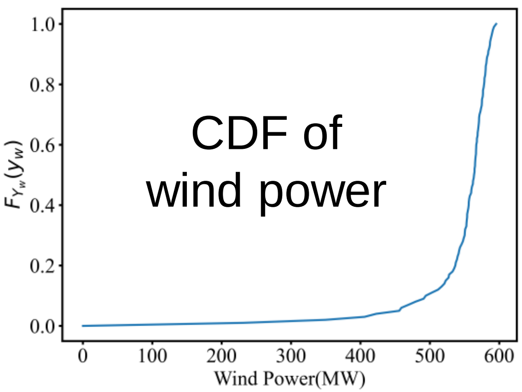
More flexible to adjust of wind and photovoltaic forecasts

Forecasting Track—Difficulty

- Quantiles of different random variables do not satisfy additivity

$$Y_w + Y_s = Z \quad \text{(total generation)}$$

(wind) (solar)



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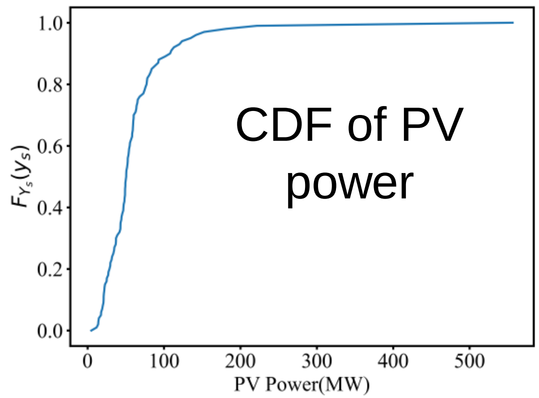

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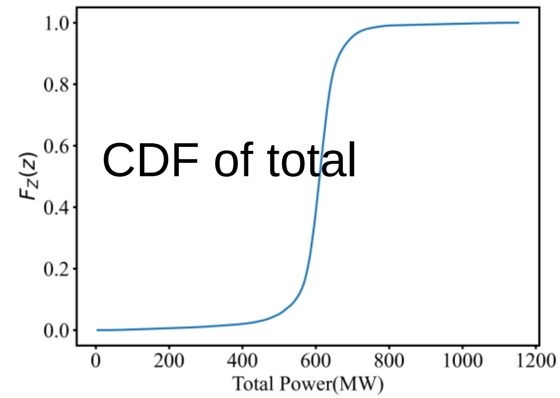
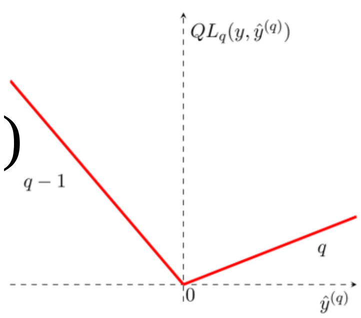


$$Q_\tau(Y_w \mid X_w) + Q_\tau(Y_s \mid X_s) \neq Q_\tau(Z \mid X_w, X_s) \quad \text{for quantile } \tau$$

- From the perspective of pinball loss L_τ

$$\min L_\tau(\hat{y}_w(\tau)) + \min L_\tau(\hat{y}_s(\tau)) \neq \min L_\tau(\hat{y}_w(\tau) + \hat{y}_s(\tau))$$



Pinball loss is a nonlinear function

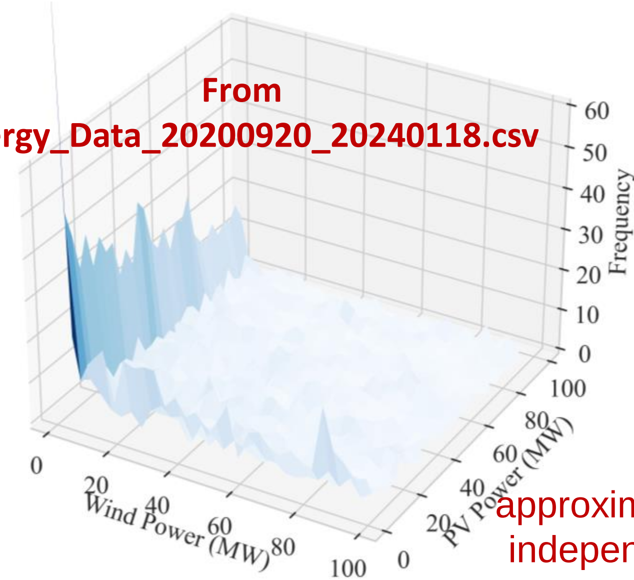
Forecasting Track—Main Solution

- Assume that wind and photovoltaic generation are independent
- If we predict probability density functions (PDF) separately, the PDF of total generation can be obtained as follow:

$$\hat{f}_Z(z) = \int_{-\infty}^{+\infty} \hat{f}_{Y_w|X_w}(y_w)\, \hat{f}_{Y_s|X_s}(z - y_w)\, dy_w$$

- By numerically integrating the PDF of total generation, we can obtain the probability distribution function (CDF)

$$\hat{F}_z(z) = \int_{-\infty}^{+\infty} \hat{f}_Z(z) dz$$



- Then the quantile forecasts:

$$\hat{z}(10\%) = \hat{F}_Z^{-1}(10\%)$$

$$\cdots$$

$$\hat{z}(90\%) = \hat{F}_Z^{-1}(90\%)$$

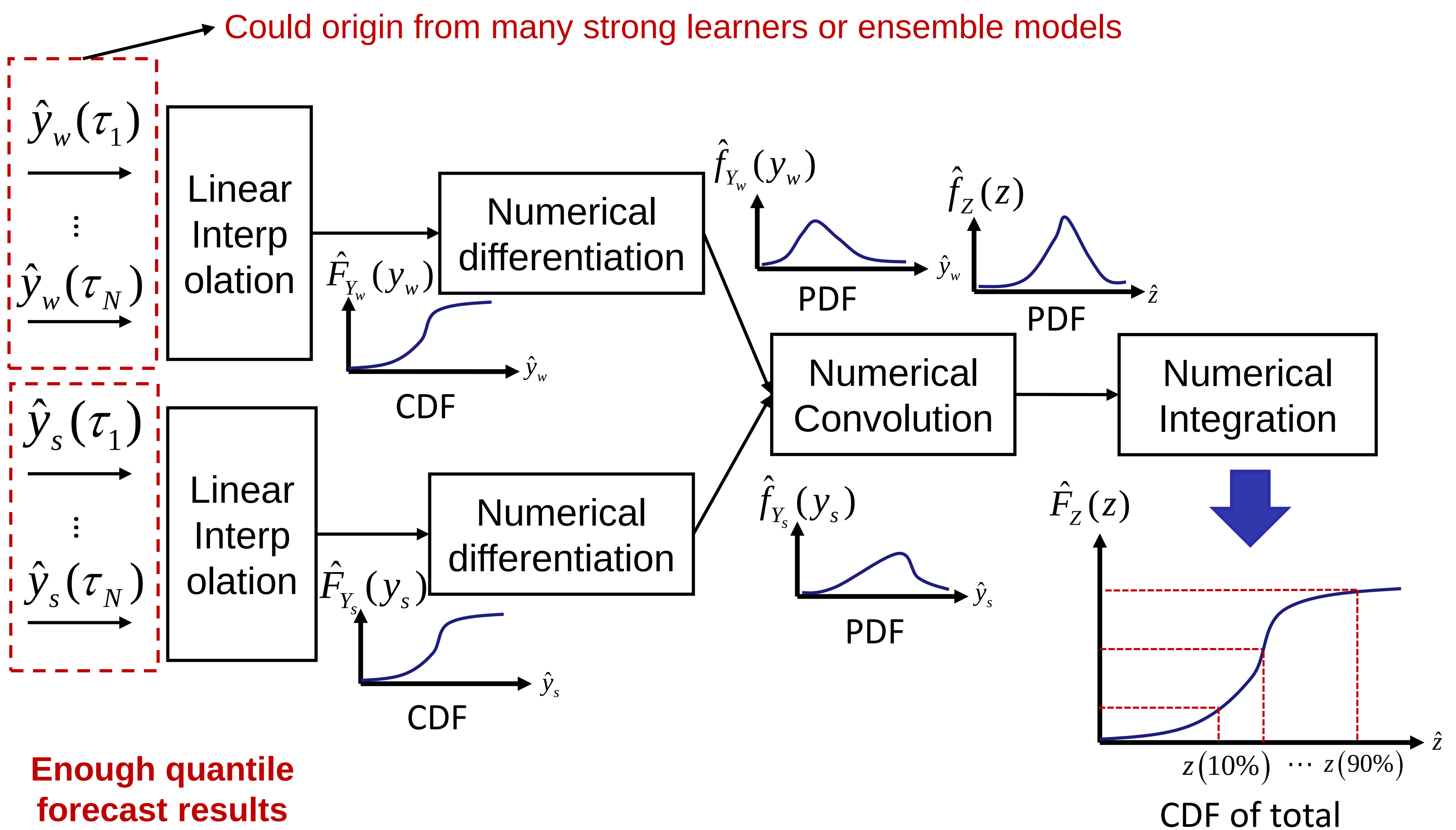
approximately independent

Mutual information

$$I(Y_w, Y_s) = \sum_{y_w, y_s} p(y_w, y_s) \log \frac{p(y_w, y_s)}{p(y_w)\, p(y_s)} = 0.0168$$

Forecasting Track—Main Solution

- A post-processing strategy to decouple wind and photovoltaic forecast models



Forecasting Track— Dataset Construction (Wind)

Original Wind Data → Data preprocessing → Feature Engineering → Expanded Features

Data preprocessing

- Outliers discarded (out of the rated capacity)
- Drop valid_time – ref_time>48 hours
- Drop NaN

Feature Engineering

- Mean, maximum and minimum 25%,75% quantile values for the weather forecast coverage area
- t-1, t, t+1 sliding window
- WindSpeed^2,WindSpeed^3

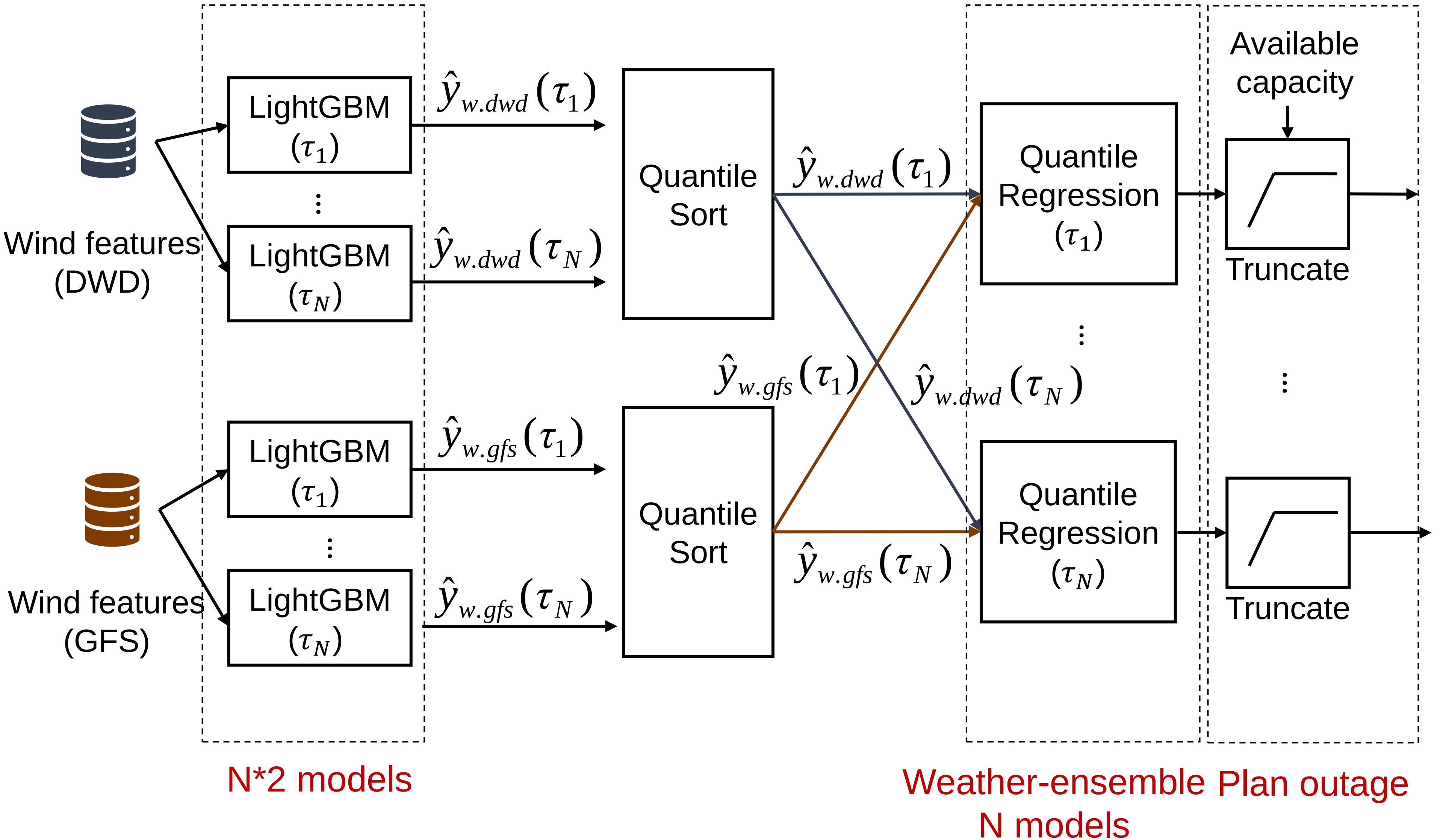
Expanded Features → Random Forest

Feature selection

ws_100_t-1
ws_100_t-1_max,
ws_100_t-1_min,
ws_100_t,
ws_100_t_max,
ws_100_t_min,
ws_100_t+1,
ws_100_t+1_max,
ws_100_t+1_min

Only Windspeed:100 used

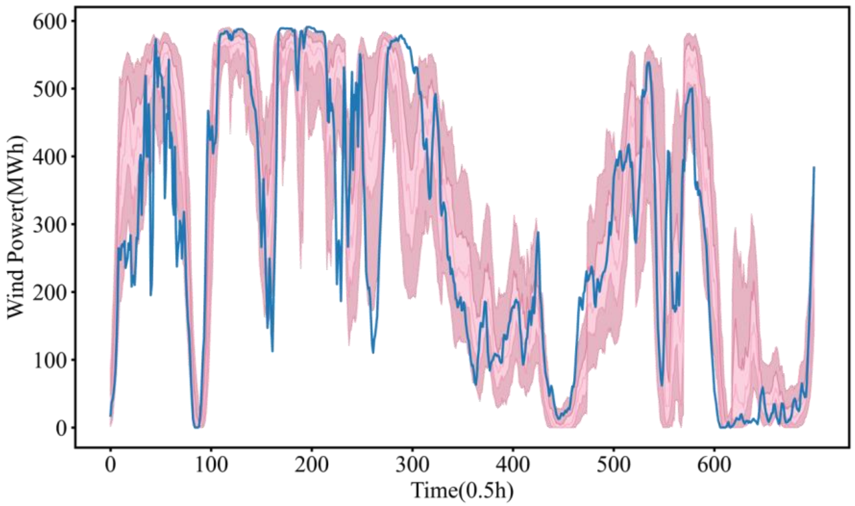
Forecasting Track— Quantile Forecast （Wind）



Forecasting Track— Quantile Forecast (Wind)

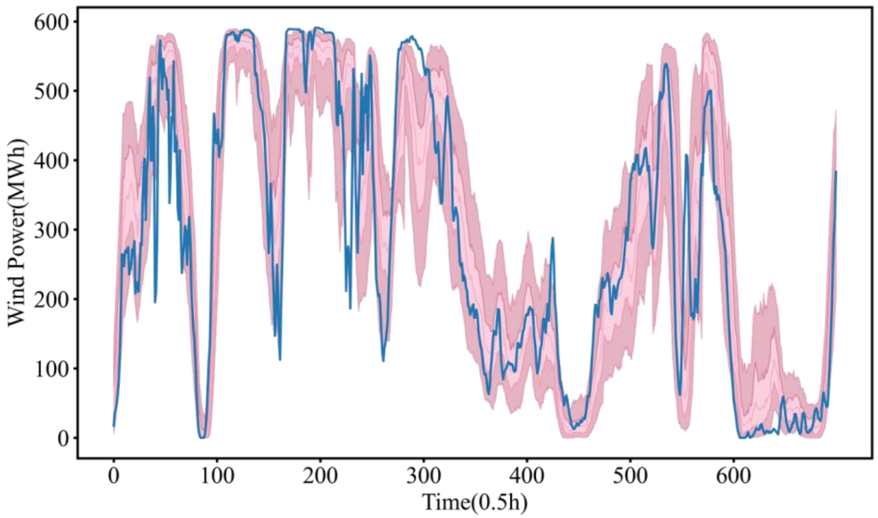
- Test period: 2023-02-01~2023-08-01, ref_time=00:00, 23≤valid_time-ref_time ≤48
- Training dataset: exclude test period
- Quantiles: 0.1%, 1%, 2%,…,99%,99.9%

Only DWD data



(Partly data displayed)

Ensembled weather



(Partly data displayed)

Mean pinball loss (all quantiles):
28.97

Mean pinball loss (all quantiles):
27.13

Forecasting Track— Dataset Construction （Solar）

Original Data → Data preprocessing → Feature Engineering → Expanded Features

Data preprocessing

- Outliers discarded (out of the rated capacity)
- Drop valid_time – ref_time>48 hours
- Drop NaN

Feature Engineering

- Mean, maximum and minimum 25%,75% quantile values for the weather forecast coverage area
- t-1, t, t+1 sliding window
- hours

Expanded Features → Random Forest

Feature selection

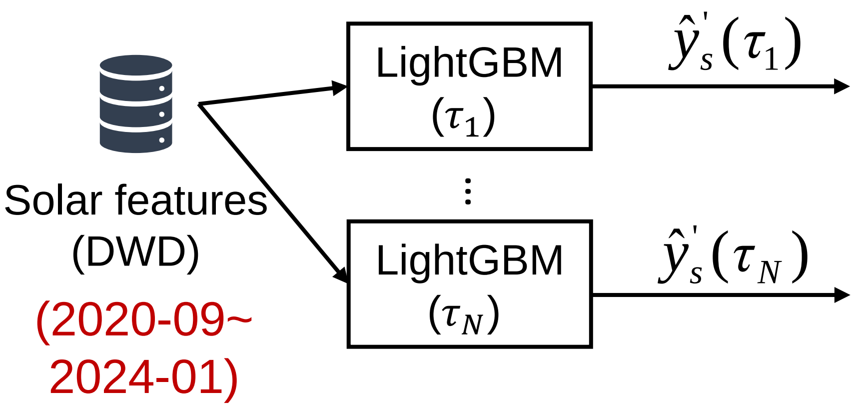
rad_t-1， rad_t-1_max， rad_t-1_min
rad_t， rad_t_max， rad_t_min
cloudcov_t-1
cloudcov_t-1_max
cloudcov_t-1 _min
cloudcov_t
cloudcov_t_max
cloudcov_t _min
hours

Forecasting Track— Quantile Forecast （Solar）

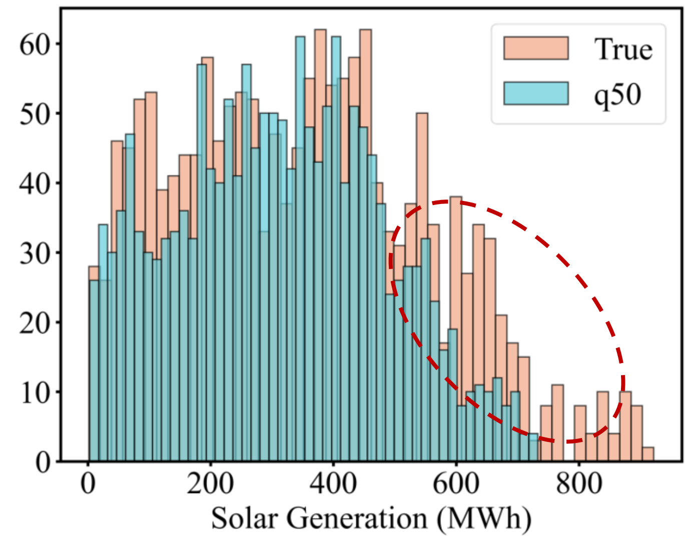
- Solar capacity changes after the start of HEFTcom

2609 MWp **2741** MWp (since 2024-02-19)

- Original framework



From 2024-03 to 2024-05



Tendency to underestimate

Forecasting Track— Quantile Forecast （Solar）

- We consider a polynomial modified model:

$$\hat{y}_s(\tau_i) = \beta_1 \hat{y}_s^{'}(\tau_i) + \beta_1 \hat{y}_s^{'2}(\tau_i) + \beta_1 \hat{y}_s^{'3}(\tau_i) \quad i = 1, \mathrm{K}\ , N$$

Modified forecast

from model trained on historical data

- Using LASSO quantile regression to modify the forecast result from the model trained on historical data

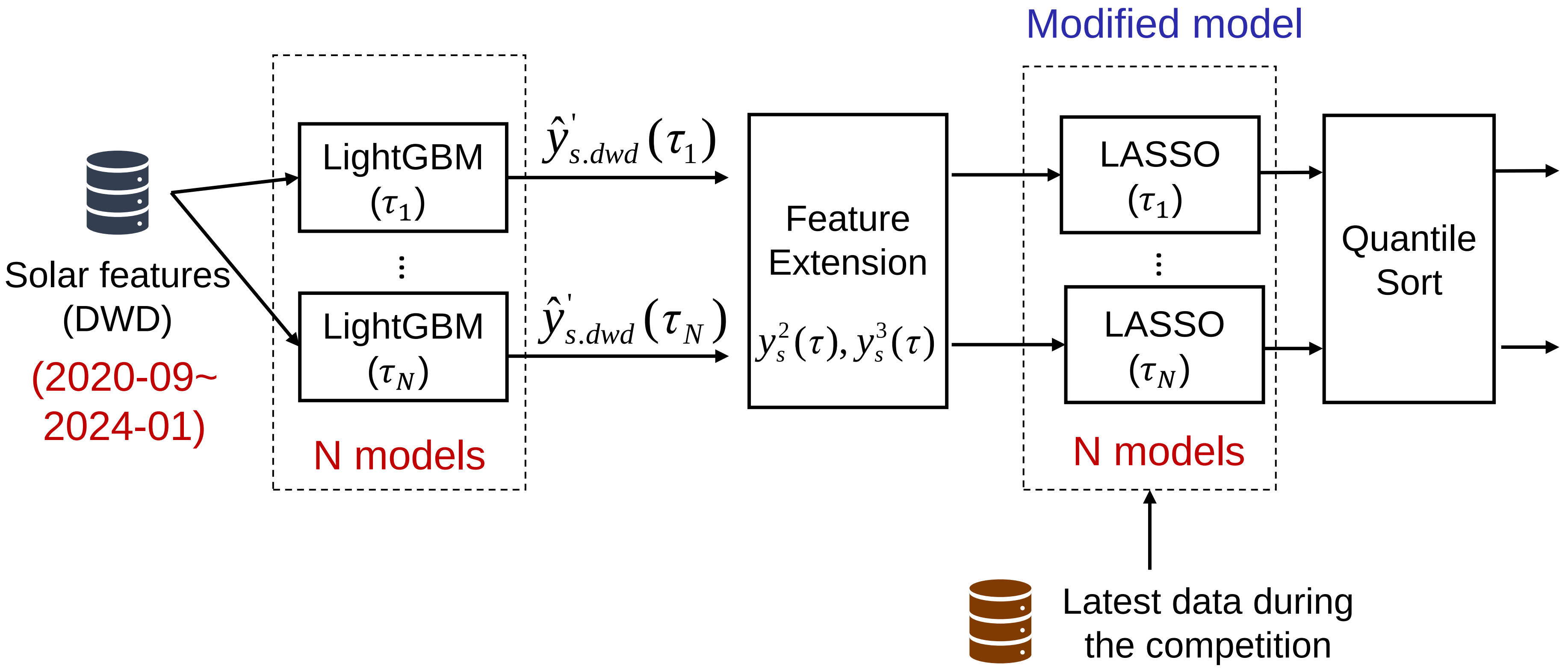
$$\min_{\boldsymbol{\beta}} L_{\tau_i}(y_s, \hat{y}_s) = \tau_i (y_s - \hat{y}_s)^+ + (1-\tau_i)(\hat{y}_s - y_s)^+ + \lambda \sum_{j=1}^{3} \left| \beta_j \right| \quad i = 1, \mathrm{K}\ , N$$

Actual generation
after 2024-02-19

L1-regularization
to make β sparser

Forecasting Track— Quantile Forecast （Solar）

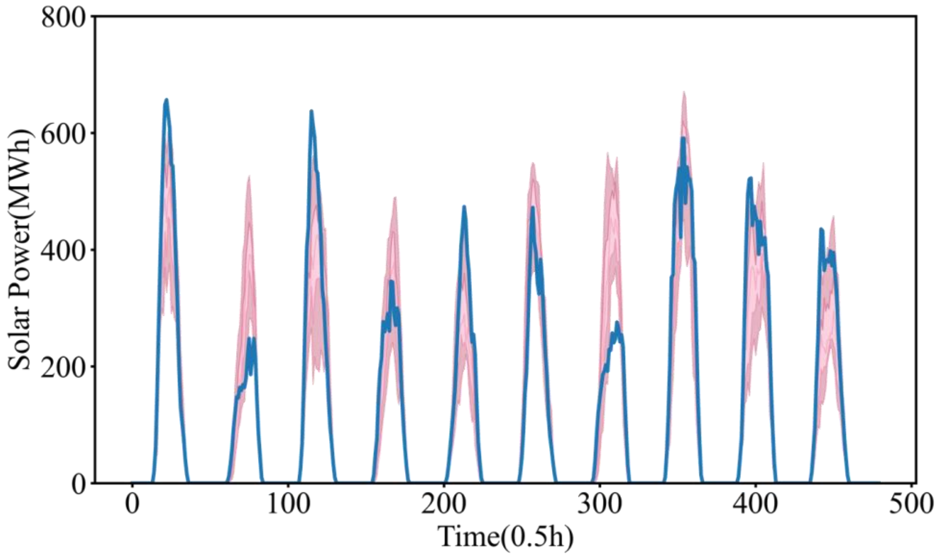
- Revised framework:



Forecasting Track— Quantile Forecast （Solar）

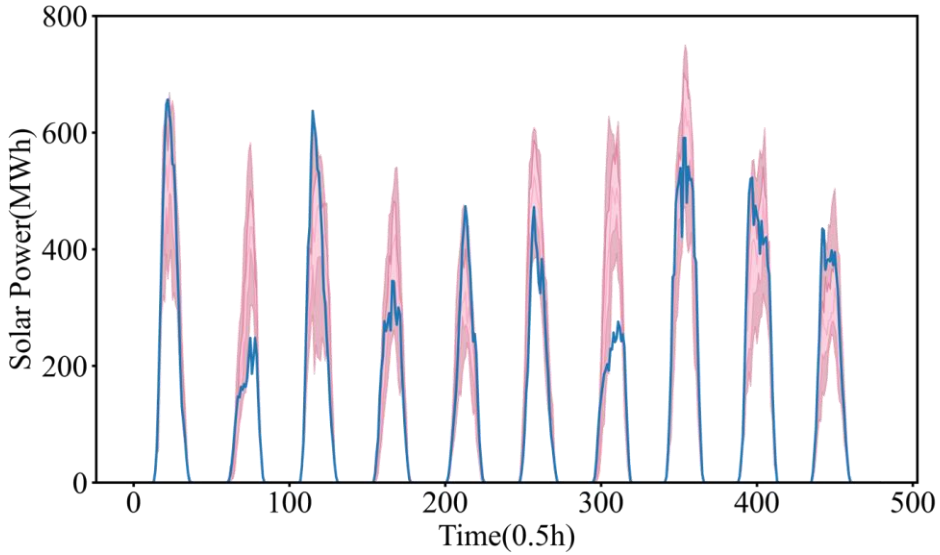
- Latest solar data: 2024-03~2024-05
- Training set : testing set = 6:4 (random spilit)

Mean pinball loss: 15.71



From model trained on historical data (partly displayed)

Mean pinball loss: **13.26**

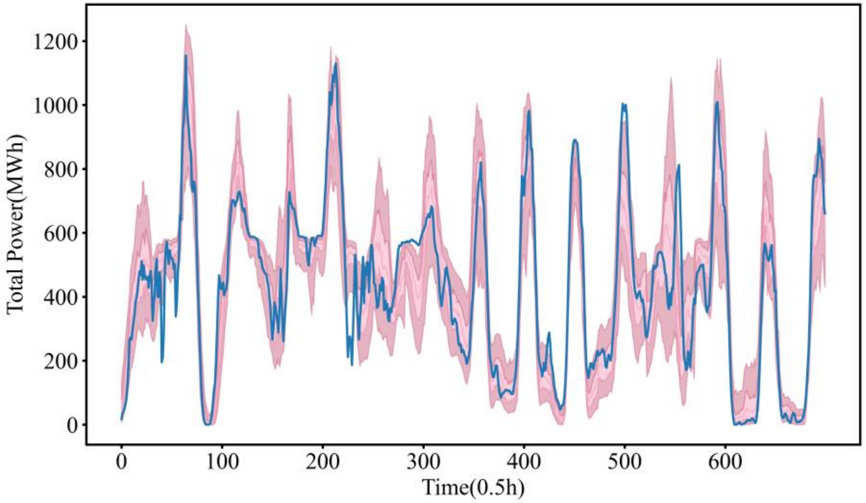


From modified model (partly displayed)

Forecasting Track— Quantile Forecast （Total）

- Test period: 2023-02-01~2023-08-01, ref_time=00:00, 23≤valid_time-ref_time ≤48
- Training dataset: exclude test period
- Quantiles: 0.1%, 1%, 2%,…,99%,99.9%

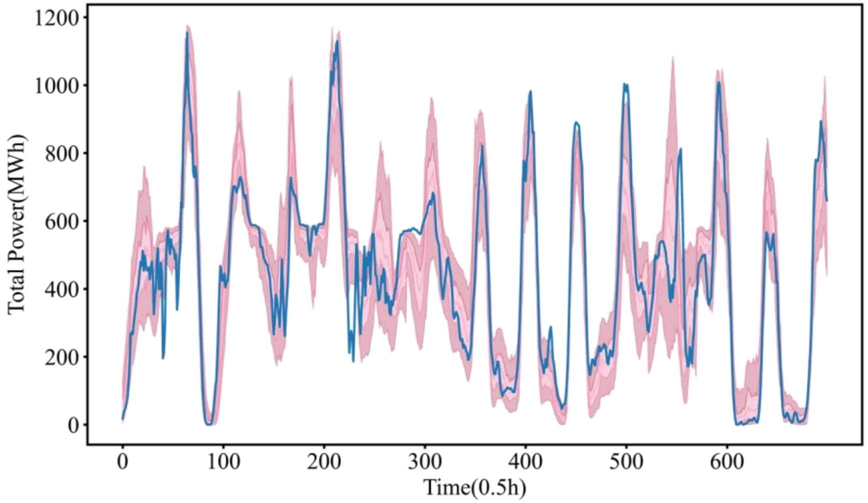
Directly add: $\hat{y}_w(\tau) + \hat{y}_s(\tau) = \hat{z}$



(Partly data displayed)

Mean pinball loss : 34.41

Quantile aggregation



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Mean pinball loss : 34.36

Forecasting Track— Hyperparameter Tuning

- Optuna framework

An open source hyperparameter optimization framework to automate hyperparameter search

```
params_grid={
    'num_leaves': trial.suggest_int('num_leaves', 100, 1000,step=100),
    "n_estimators": trial.suggest_categorical("n_estimators", [500,1000,2000]),
    'max_depth': trial.suggest_int('max_depth', 3, 12),
    'min_data_in_leaf': trial.suggest_int('min_data_in_leaf', 200, 10000,step=100),
    'learning_rate': trial.suggest_float('learning_rate', 0.01, 0.3),
    'lambda_l1': trial.suggest_int('lambda_l1', 0, 100,step=10),
    'lambda_l2': trial.suggest_int('lambda_l2', 0, 100,step=10),
    "random_state": 2048,
    'verbose':-1,
    'objective':'quantile  ',
    'alpha':quantile/100
    }
```

Search q50 wind and solar model only

Trading Track— Rules

- The revenue:

$$F(\hat{z}_b) = \boxed{\pi_{da}\hat{z}_b} + \boxed{\pi_{ss}(z-\hat{z}_b)} - \boxed{0.07(z-\hat{z}_b)^2}$$

Day-ahead market revenue

Balancing market revenue

Penalty of generation deviation

- We define the price difference:

$$\pi_{da} - \pi_{ss} \triangleq \pi_d$$

$$F(\hat{z}_b) = \underbrace{\boxed{\pi_{ss} z}}_{\text{constant}} + \underbrace{\boxed{\pi_d \hat{z}_b - 0.07(z-\hat{z}_b)^2}}_{\text{Needs to maximize}}$$

Notation	
π_{da}	Day-ahead price
π_{ss}	Balancing price
z	Actual generation
$\hat{z}_b$	Bidding volume (decision variable)

Accurate estimation of price difference π_d and actual generation z is crucial to bidding decision

Trading Track— Strategy

- The optimal bidding decision $\hat{z}_b^*$ satisfies:

Karush-Kuhn-Tucker (KKT) Conditions

$$\begin{cases} \nabla_{\hat{z}_b} F(\hat{z}_b^*) = \pi_d + 0.14(z - \hat{z}_b^*) - \lambda_1 + \lambda_2 = 0 \\ -\hat{z}_b^* \leq 0 \quad \text{(lower bound)} \\ \hat{z}_b^* \leq 1800 \quad \text{(upper bound)} \\ -\lambda_1 \hat{z}_b^* = 0 \\ \lambda_2(\hat{z}_b^* - 1800) = 0 \end{cases}$$

(complementary relaxation)

- Given the forecast result of price difference $\hat{\pi}_d$ and total generation $\hat{z}$ the optimal bidding strategy:

$$\hat{z}_b^* = \begin{cases} \hat{z} + 7.14\hat{\pi}_d & \lambda_1 = 0, \lambda_2 = 0 \\ 0 & \lambda_1 \neq 0, \lambda_2 = 0 \\ 1800 & \lambda_1 = 0, \lambda_2 \neq 0 \end{cases}$$

Trading Track— Decision Loss

- Assuming the price difference and total generation forecast are known, the optimal decisions are

$$\hat{z}_b^* = \hat{z} + 7.14\hat{\pi}_d \quad \text{(in most cases)}$$

- The actual revenue:

$$F(\hat{z}_b^*) = \pi_d \hat{z}_b^* - 0.07(z - \hat{z}_b^*)^2 + \pi_{ss} z$$

- The theoretical optimal revenue (under unbiased forecast):

$$F(z_b^*) = \pi_d z_b^* - 0.07(z - z_b^*)^2 + \pi_{ss} z$$

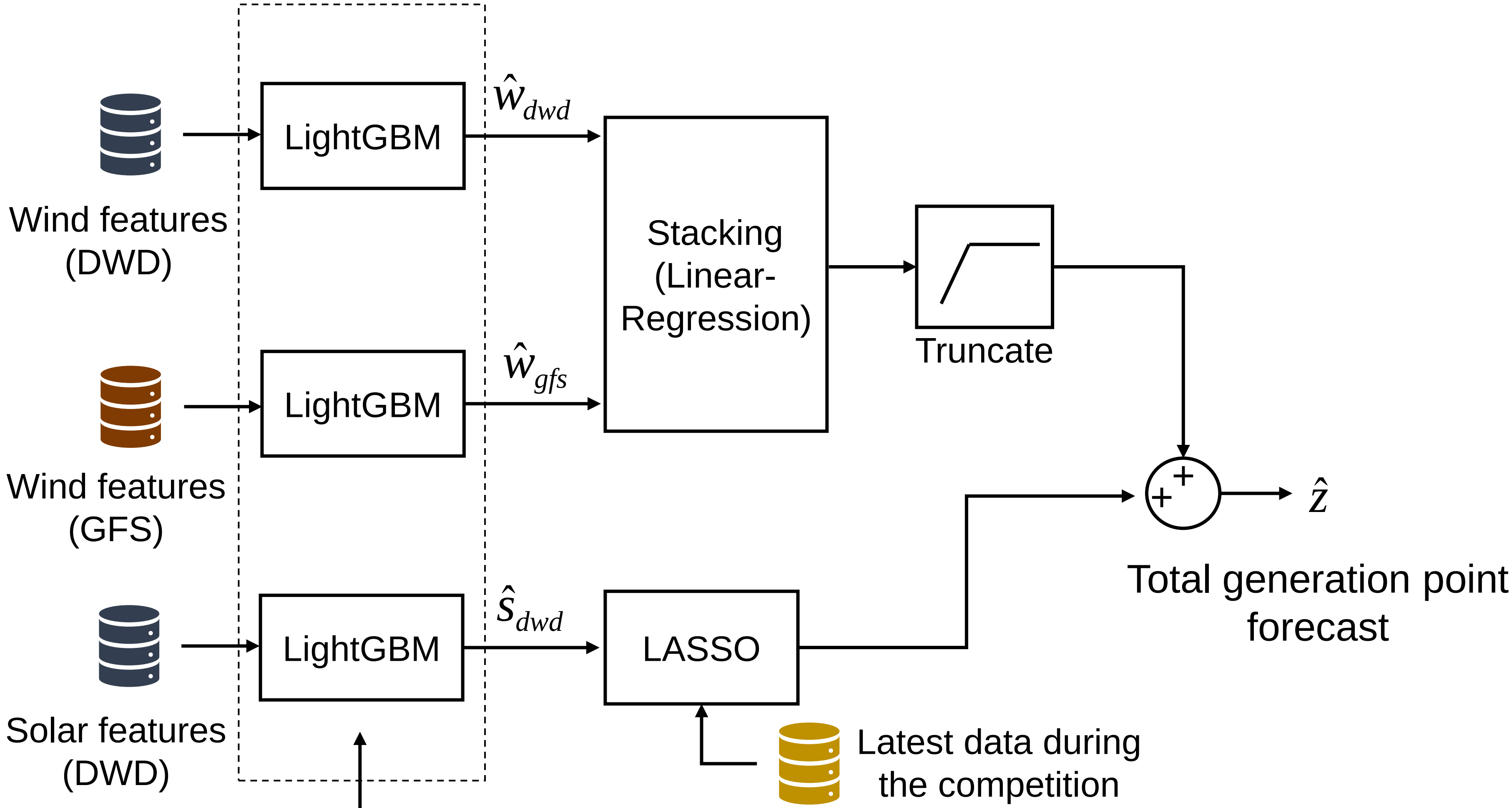
where

$$z_b^* = z + 7.14\pi_d$$

- The gap between the actual revenue and the theoretical optimal revenue is

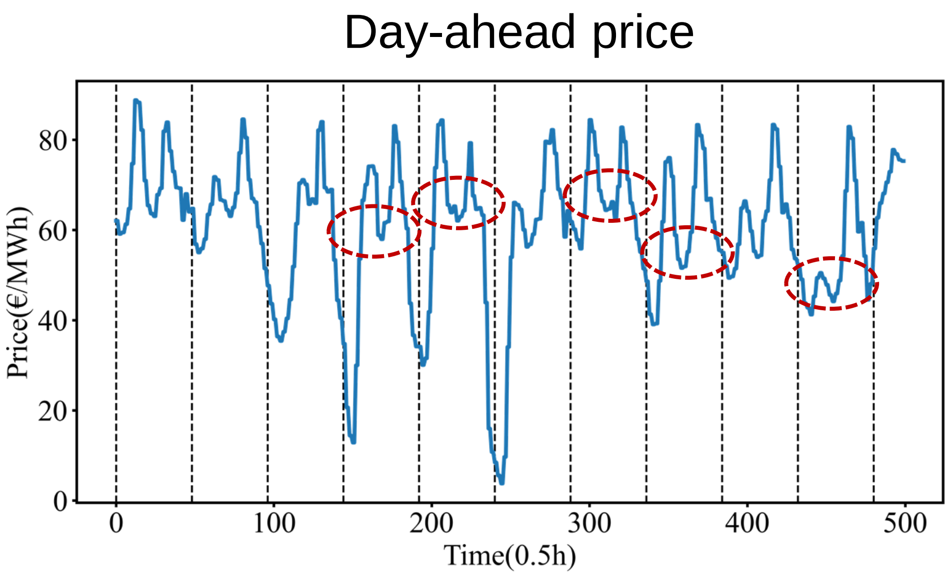
$$\underbrace{\boxed{F(z_b^*) - F(\hat{z}_b^*)}}_{\text{Decision loss}} = 0.07\underbrace{\boxed{\left(z - \hat{z}\right)^2}}_{\text{MSE}} + 3.57\underbrace{\boxed{(\pi_d - \hat{\pi}_d)^2}}_{\text{MSE}} + \underbrace{\boxed{(z - \hat{z})(\pi_d - \hat{\pi}_d)}}_{\text{Coupled term}}$$

Trading Track— Point Forecast Model

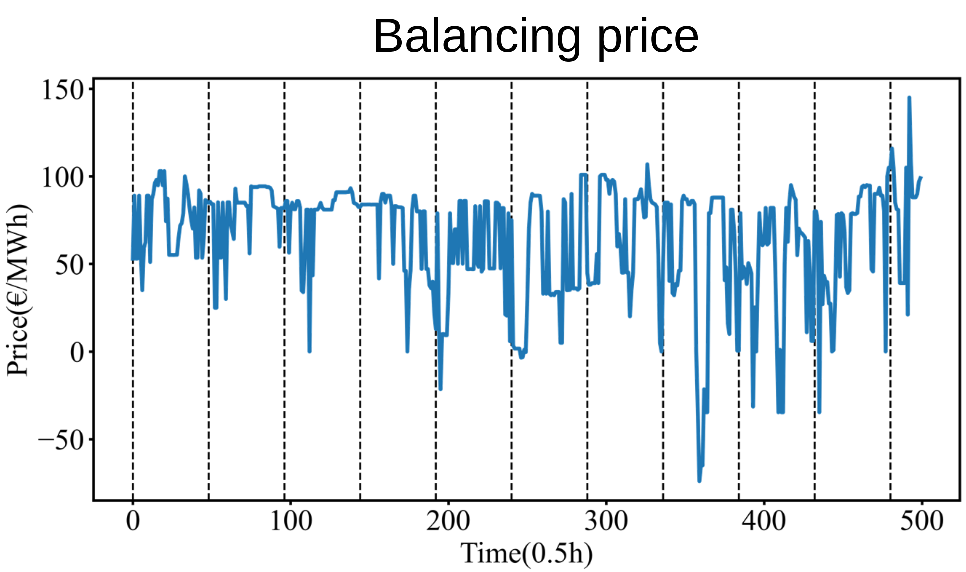


MSE Loss $$\min_{\theta} \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Trading Track— Prices

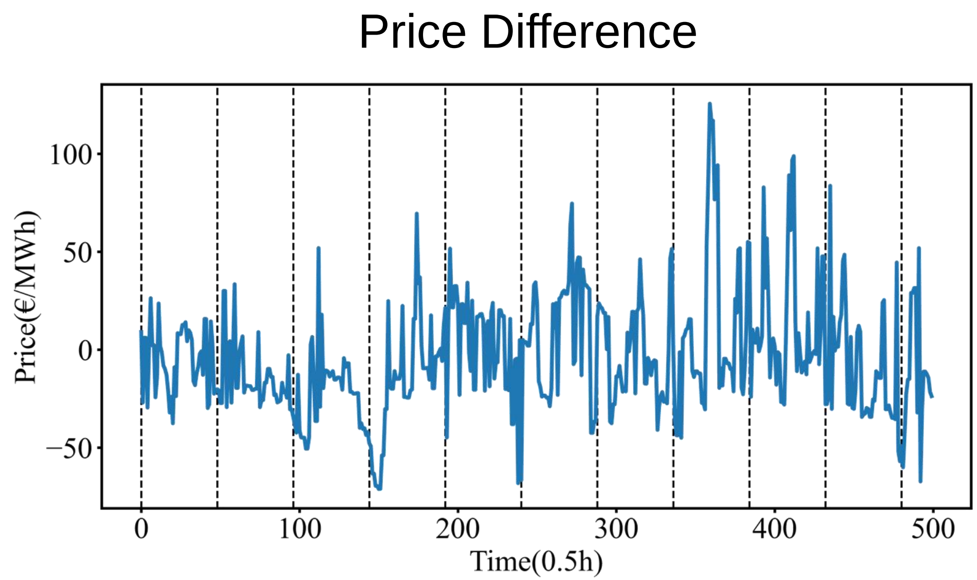


- Daily periodicity
- Similar daily fluctuation patterns (related to PV generation, load patterns)
- Hours features is useful

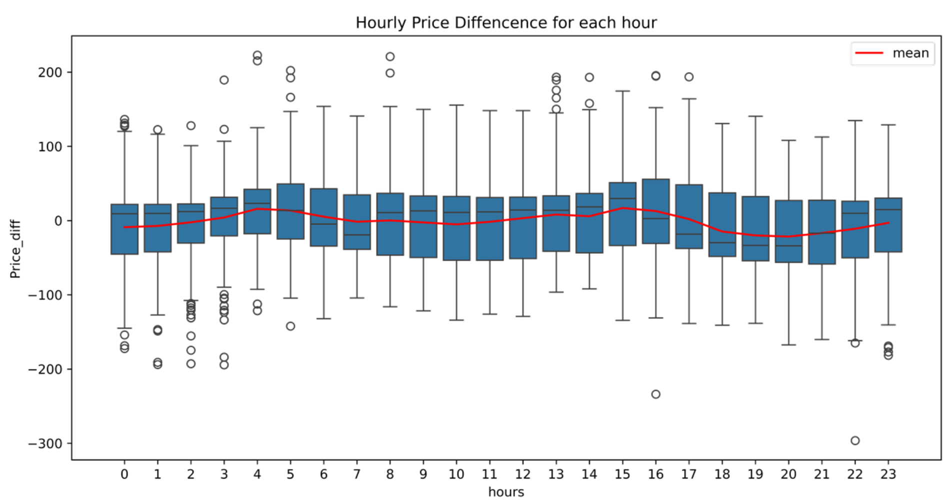


- No apparent periodicity
- Random fluctuations
- Related to the unbalance in real-time market caused by renewable generation and load

Trading Track— Difficulty of Price Forecast



- High signal-to-noise ratio (SNR)
- Price difference updates are delayed by 4-5 days
- Historical electricity demand forecasting is unavailable



- The mean value of the price difference is still related to the hours of day.

Trading Track— Stochastic Programming

- Probabilistic modeling of uncertain price difference with hour *t* as a covariate, we construct a stochastic programming problem

$$
\begin{aligned}
\max J_t(\hat{z}_b) &= \sum_{s\in\Omega} p_s(\pi_{d.s} \mid t)[\pi_{d,s}\hat{z}_b - 0.07(\hat{z}-\hat{z}_b)^2] \\
&= \sum_{s\in\Omega} p_s(\pi_{d.s} \mid t)\pi_{d,s}\hat{z}_b - 0.07(\hat{z}-\hat{z}_b)^2 \sum_{s\in\Omega} p_s(\pi_{d.s} \mid t) \\
&= \overline{\pi}_{d,t}\hat{z}_b - 0.07(\hat{z}-\hat{z}_b)^2
\end{aligned}
$$

- The final trading strategy is:

$$
\hat{z}_{b,t} = \begin{cases} 0 & \hat{z} + 7.14\overline{\pi}_{d,t} \le 0 \\ 1800 & \hat{z} + 7.14\overline{\pi}_{d,t} \ge 1800 \\ \hat{z} + 7.14\overline{\pi}_{d,t} & others \end{cases}
$$

Rolling average of price differentials over the past two months

MSE-oriented forecast

Relying only on past electricity price time series

Trading Track— Ablation Study

- Test period: 2023-02-01~2023-08-01, ref_time=00:00, 23≤valid_time-ref_time ≤48
- Training dataset: exclude test period

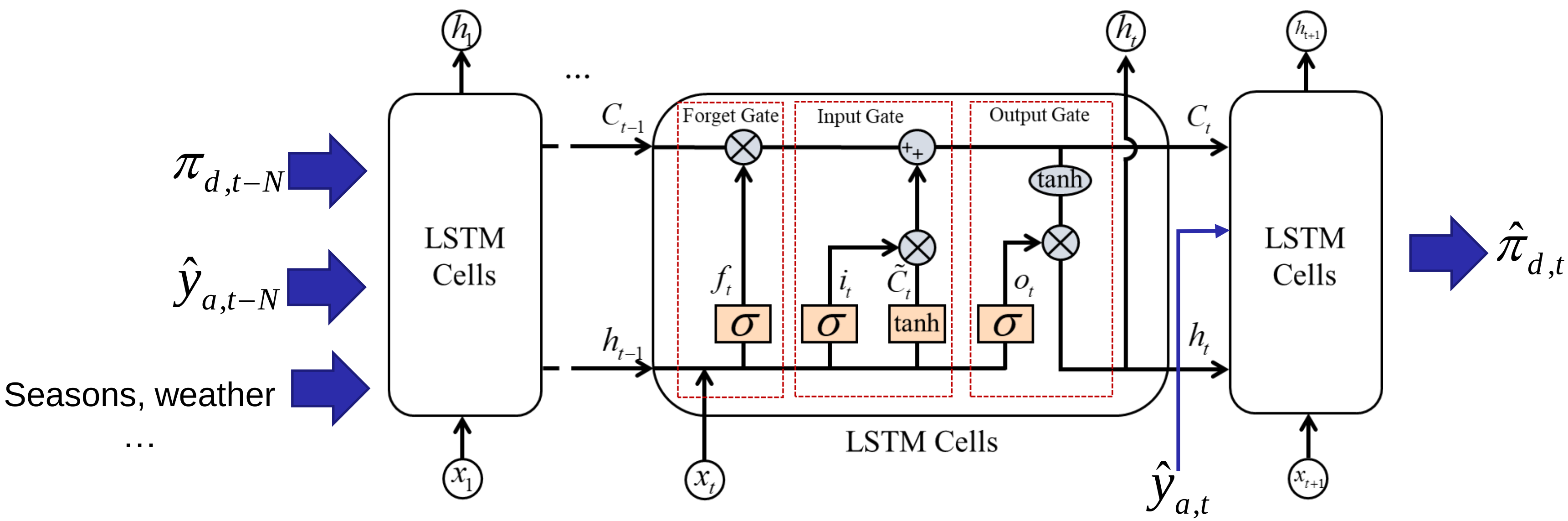
Results

Methods	MAE	RMSE	Mean Daily Revenue (EUR)	Improvement
$\hat{z}_b^* = \hat{z}(q50)$ Open benchmark	87.0	130.4	1711694.5	/
$\hat{z}_b^* = \hat{z}(MSE)$	89.0	128.6	1713914.7	0.13%
$\hat{z}_{b,t}^* = \hat{z}_t(q50) + 7.14\bar{\pi}_{d,t}$	/	/	1718821.93	0.42%
$\hat{z}_{b,t}^* = \hat{z}_t(MSE) + 7.14\bar{\pi}_{d,t}$	/	/	**1719510.84**	**0.46%**

- Both MSE-oriented point forecasting and stochastic programming are helpful in boosting revenue

What's Next— Value-Oriented Trading

- From the perspective of time series forecasting
- Minimizing the decision loss



- The loss function is constructed as:

$$\min_{\theta} L = \sum_{i=1}^{N_i} 3.57(\pi_{d,i} - \hat{\pi}_{d,i})^2 + (z_i - \hat{z}_i)(\pi_{d,i} - \hat{\pi}_{d,i})$$

Consider both the MSE of price difference and the coupling term

Discussion

Tricks

- Quantile Sort
- Train-test (try to simulate the practical situation)
- Online data management: save the daily forecasts and inputs data
- Data ensemble **>** model ensemble with same input

Future Work

- More accurate end-to-end forecast for trading
- Point forecast (trading) -> end-to-end probabilistic forecast then trading (CVaR, robust optimization)
- Neural network application in forecasting

THANKS!

How NOT to win a forecasting competition

Gergo BARTA
Team UI BUD
barta.gergo.bme@gmail.com

Competitive background

Participating in data science competitions since 2013

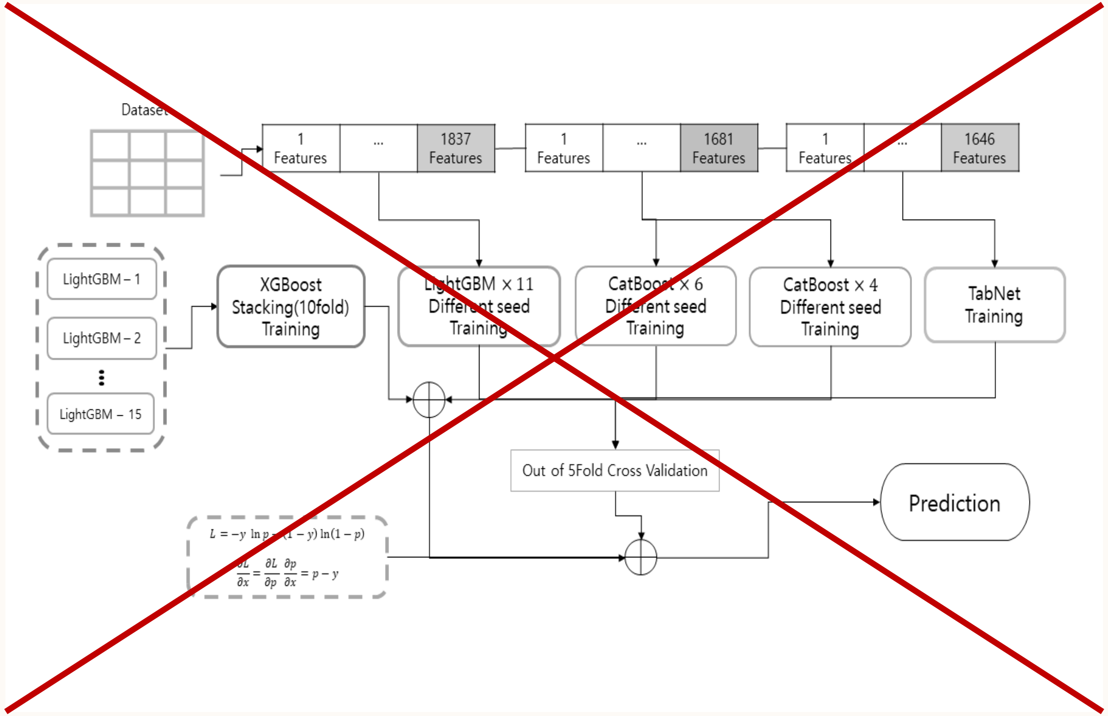
2024 Hybrid Energy Forecasting And Trading Competition – Forecasting track: 2nd / 66
2024 Hybrid Energy Forecasting And Trading Competition – Trading track: 4th / 66
2021 Shell.ai Hackathon for Sustainable and Affordable Energy: 18th / 787 (team effort)
2021 Western Power Distribution's POD Data Science Challenge: 5th / 55 (team effort)
2020 EEM20 Wind Power Production Forecasting: 6th / 10
2018 BigDEAL Probabilistic Daily Peak Load Forecasting: 4th / 39
2018 RWE Npower Gas Demand Forecasting Challenge: 4th / 18
2018 RTE Winter Electricity Demand Forecast Competition (Probabilistic): 16th / 158
2018 RTE Winter Electricity Demand Forecast Competition (Deterministic): 22nd / 269
2017 RWE Npower Electric Load Forecasting Challenge: 8th / 46
2017 RTE Day-ahead Load Forecasting Competition: 23rd / 477
2017 ECML-PKDD Multi-Plant Photovoltaic Energy Forecasting Challenge: 6th / 11
2017 IEEE Global Energy Forecasting Competition Load forecasting track: 3rd / 73 (team effort)
2017 EEM Forecast Competition – Wind Power Forecasting: 5th / 26
2015 RWE Npower Electric Load Forecasting Challenge: 2nd / 33
2015 CrowdANALYTIX Predict daily spot price of copper: 1st / 261 (tied, team)
2015 ECML-PKDD Bike Sharing Challenge: 10th / 23
2015 RWE Npower Gas Demand Forecasting Challenge: 4th / 32
2014 NIH Tox21 Data Challenge: 1st / 40 in 3 out of 12 tracks
2014 IEEE Global Energy Forecasting Competition Wind power forecasting track: 2nd place (team effort)
2014 IEEE Global Energy Forecasting Competition Solar power forecasting track: 2nd place (team effort)
2014 TEXATA Big Data Analytics World Championships: semi-finalist
2013 PRUDSYS Data Mining Cup: 1st place (team) in 1 out of 2 tracks
2013 CrowdANALYTIX Predict the Marketing Buzz: 7th / 123
2013 CrowdANALYTIX Predict the next phone call: 5th / 196 (team effort)

Sprinters don’t win marathons.

01

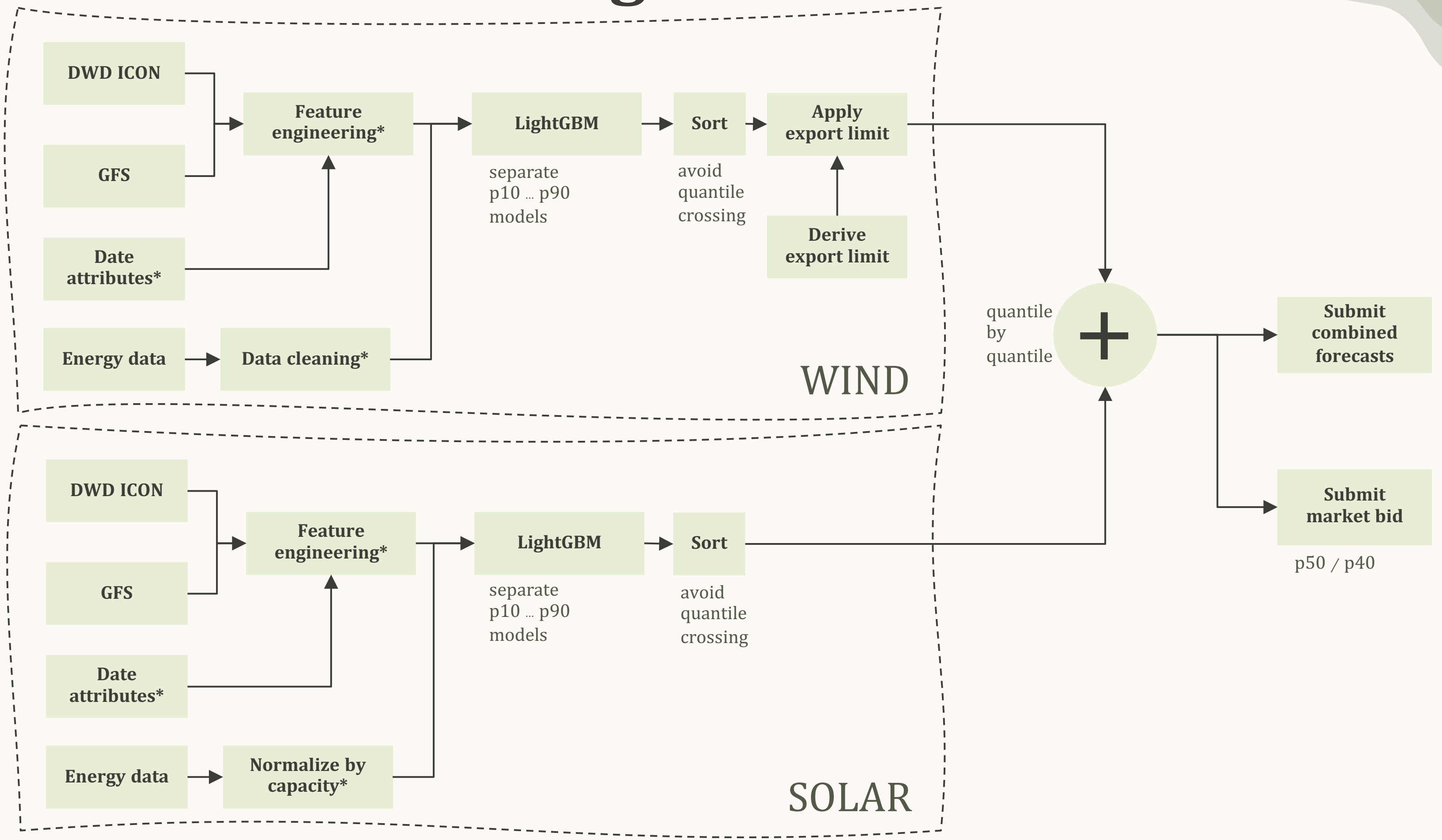
Forecasting track 🥈

Architecture design



Requirements
- consistency over peak accuracy
- avoid overfitting
- adjustable complexity

Architecture design



Feature engineering – Solar

DWD ICON

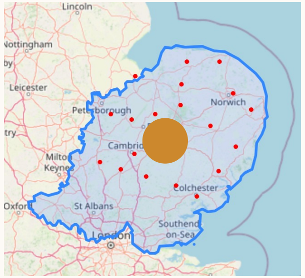
- **Temperature**
- **DownwardRadiation**
- **CloudCover**

GFS

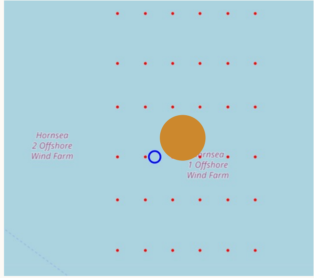
- **DownwardRadiation**
- **CloudCover**
- **Temperature**

Aggregate over grid points

mean
std



PES10
20 grid pts

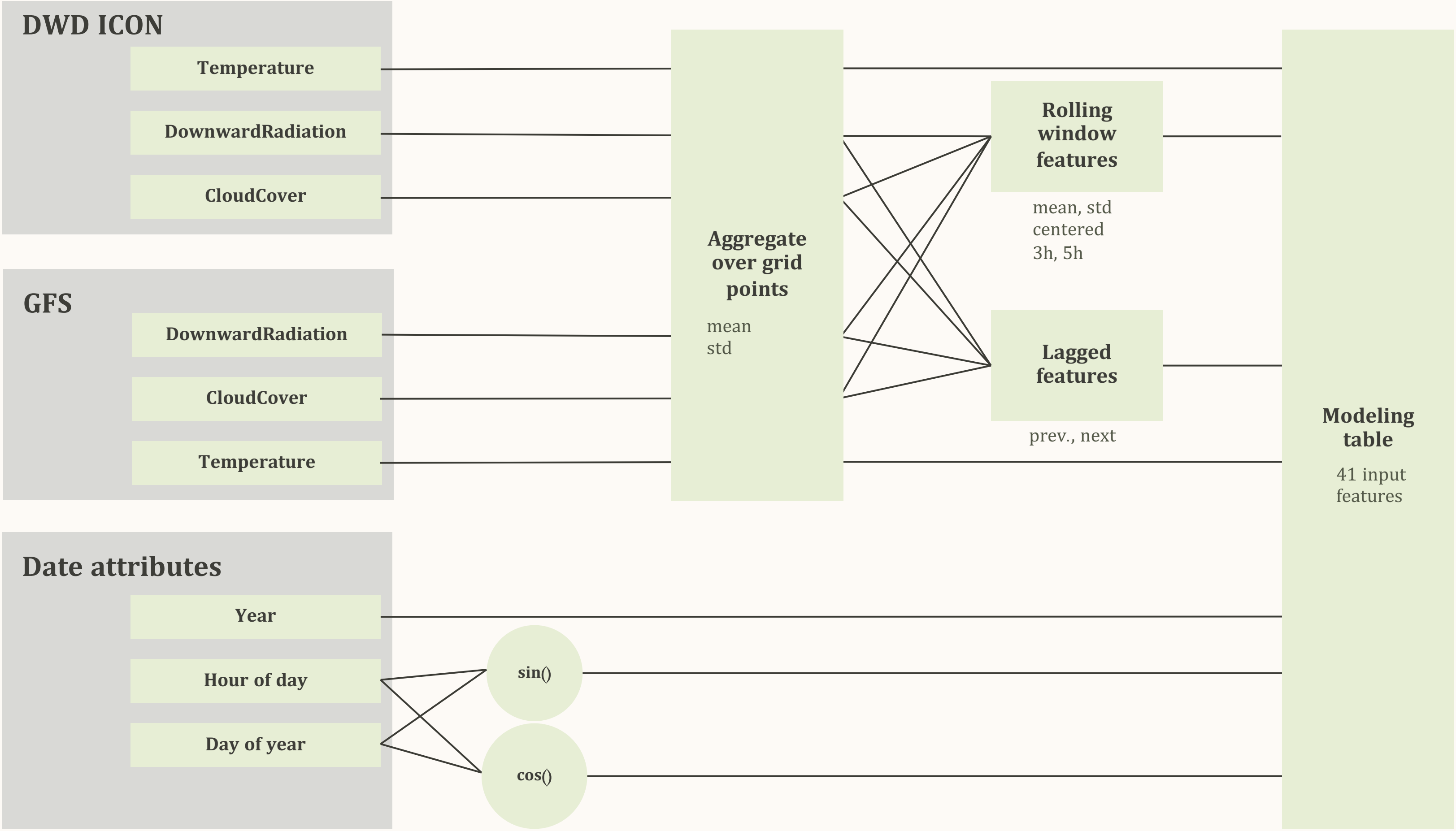


Hornsea 1
36 grid pts

Ideas never implemented:

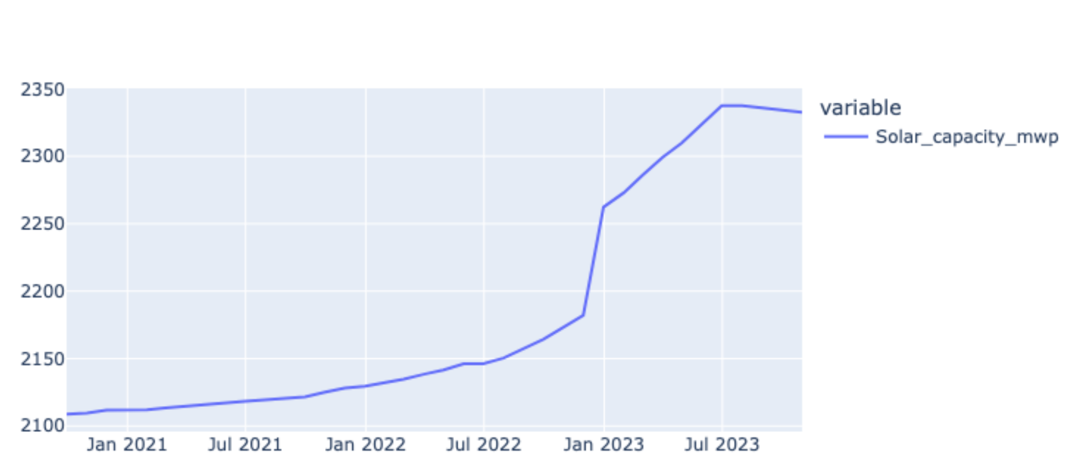
- ECMWF
- weather station selection

Feature engineering – Solar



Energy data – Solar

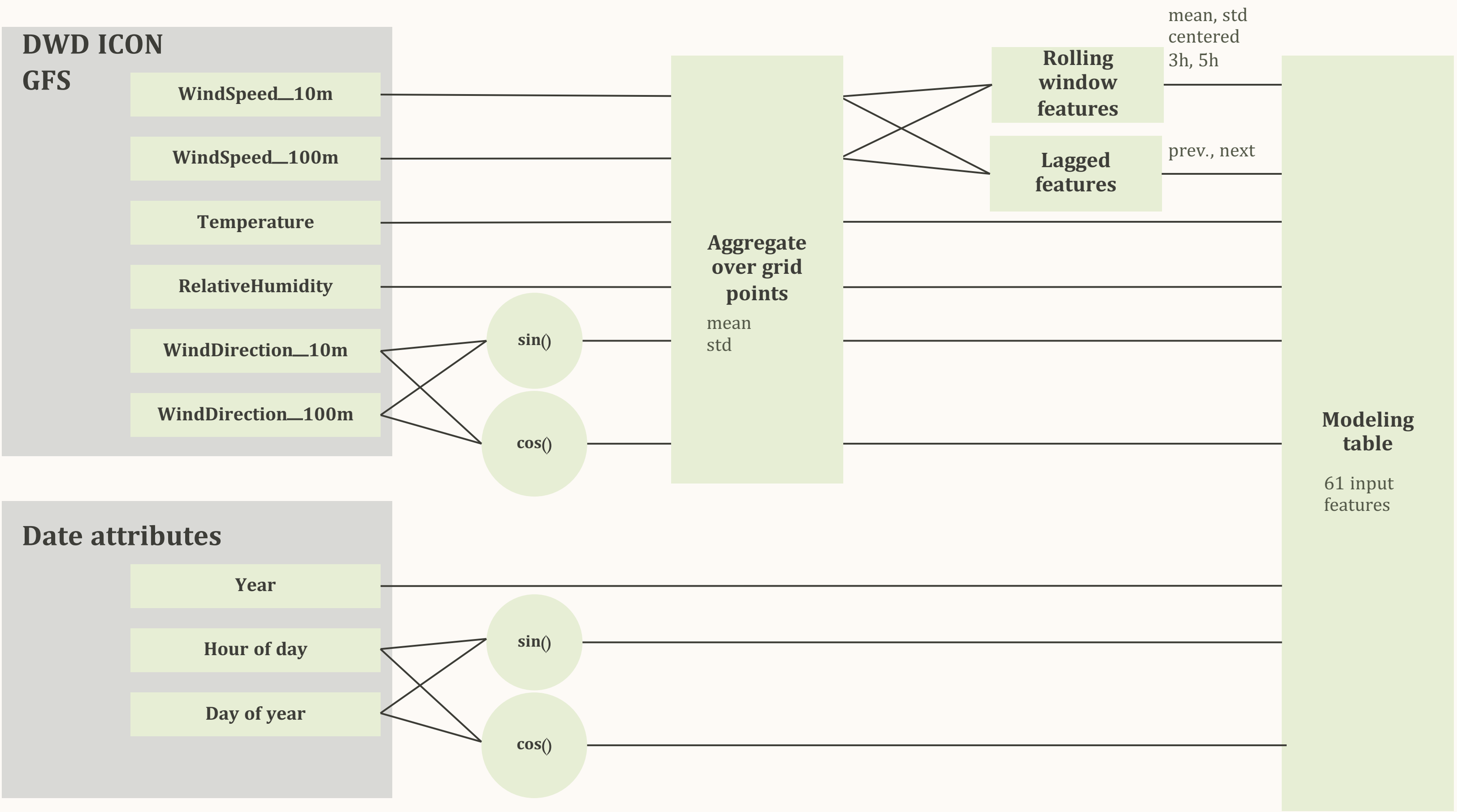
- Relatively high data quality
- Normalize target
    - by estimated total capacity
    - not installed capacity



Ideas never implemented:

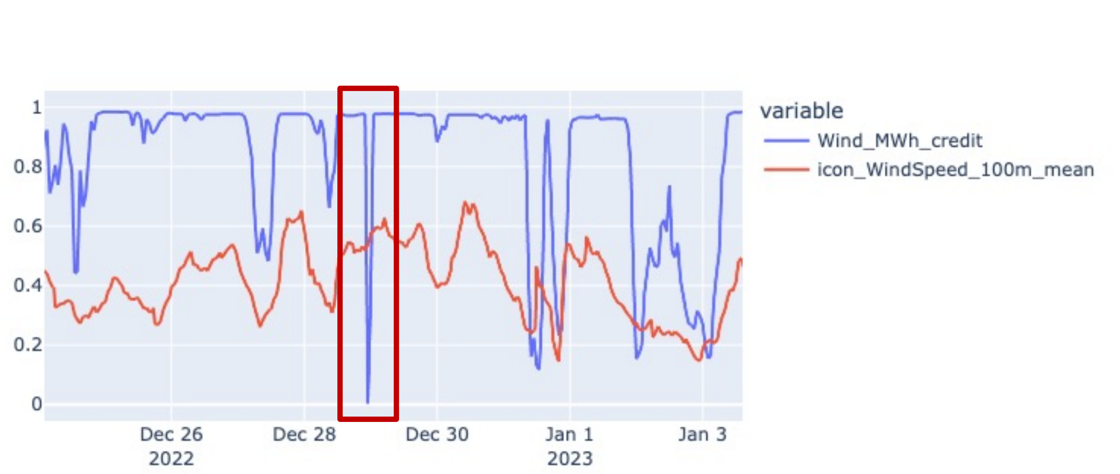
- re–train with additional data Feb–May 2024

Feature engineering – Wind



Energy data – Wind

- Curtailment post mid–Jan 2024
- Data quality issues
    - intermittent curtailment pre–2024
    - manual removal of data points



Ideas never implemented:

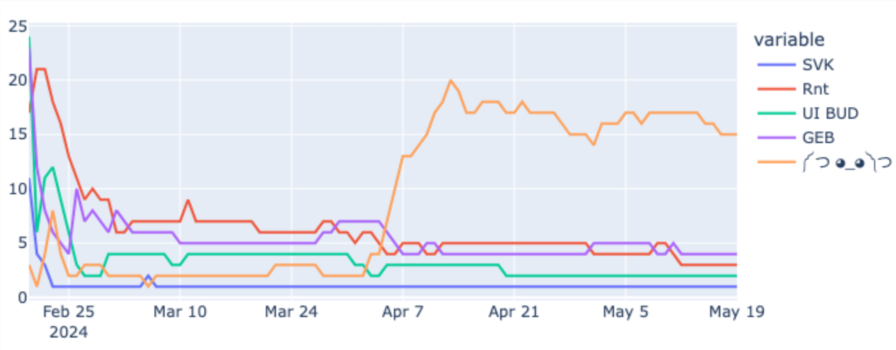
- Cap target data instead of forecasts

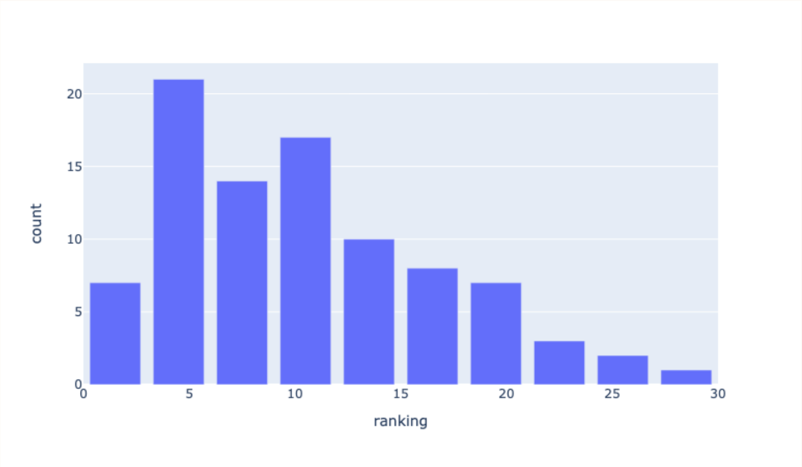
Personal approach

- One man show
- No additional data used
    - planned but never implemented
- No multi–model ensemble
    - planned but never implemented
- Models built on personal laptop
- Submission automated but seldom used

Key takeaways 🥈

- Start early and start strong
  - bring your A game from Day 1
  - consistency over peak accuracy
  - feature engineering & data quality over complex models
- Build a robust forecasting system
  - get ready for any scenario
  - missing, duplicated, delayed inputs (NWP)
  - misleading curtailment info
  - log everything
- Stay involved
  - avoid fatigue
  - manual submission every day(!)
  - monitor the leaderboard(!)





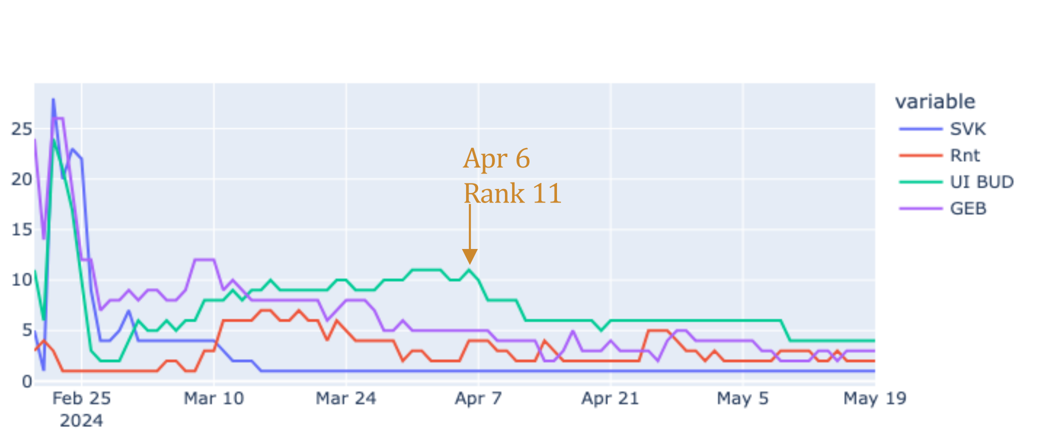
02

Trading track

4th

Energy trading track

- Disclaimer: I am a forecaster not a trader
- Initially p50 (baseline solution)
- Historical assessment on Feb–Mar forecasts
    - p40 – risk aversion pays off



Ideas never implemented:

- adjust risk taking by time of day

Key takeaways 4th

- Successful trading starts with good forecasts

Good forecast → **p40 / p50** → **Profit**

Thanks!

Do you have any questions?

barta.gergo.bme@gmail.com

linkedin.com/in/gergobarta

REint

Building AI Weather Models for Renewables

reint.ai
contact@reint.ai

The Team

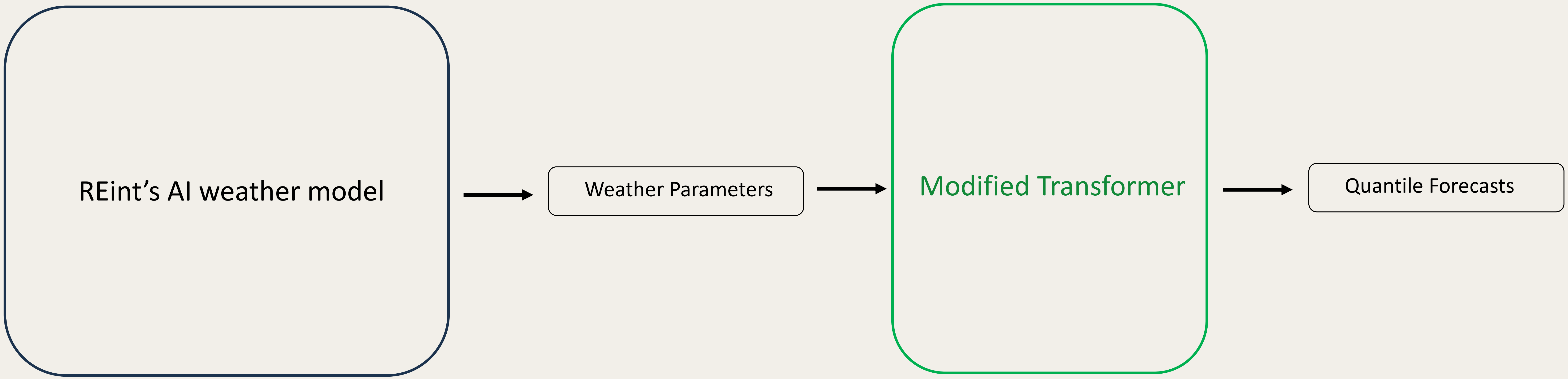
TARUN RAJ

tarun@reint.ai

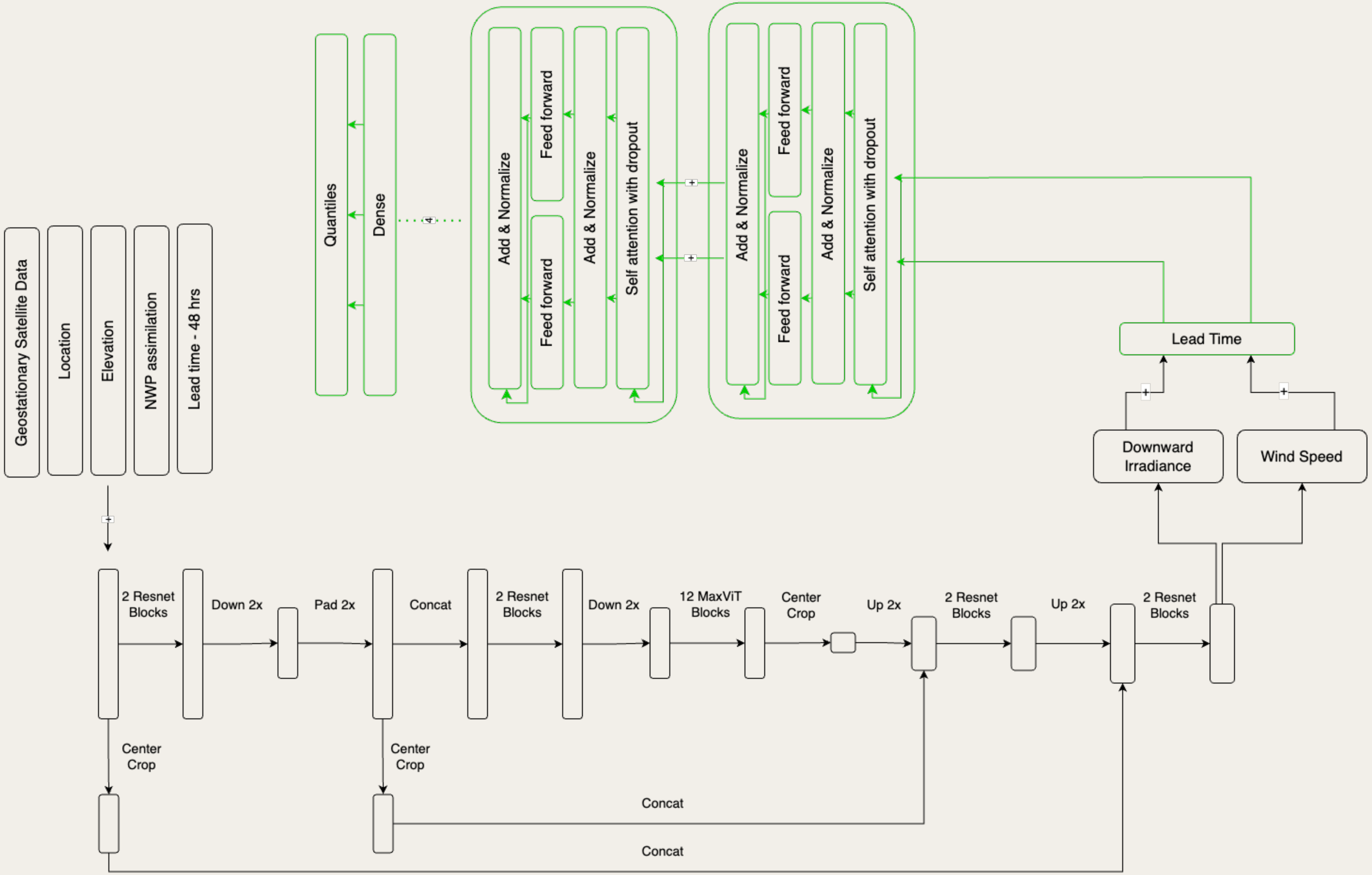
HARISANKAR HARIDAS

hari@reint.ai

Forecasting Task Architecture - Summary

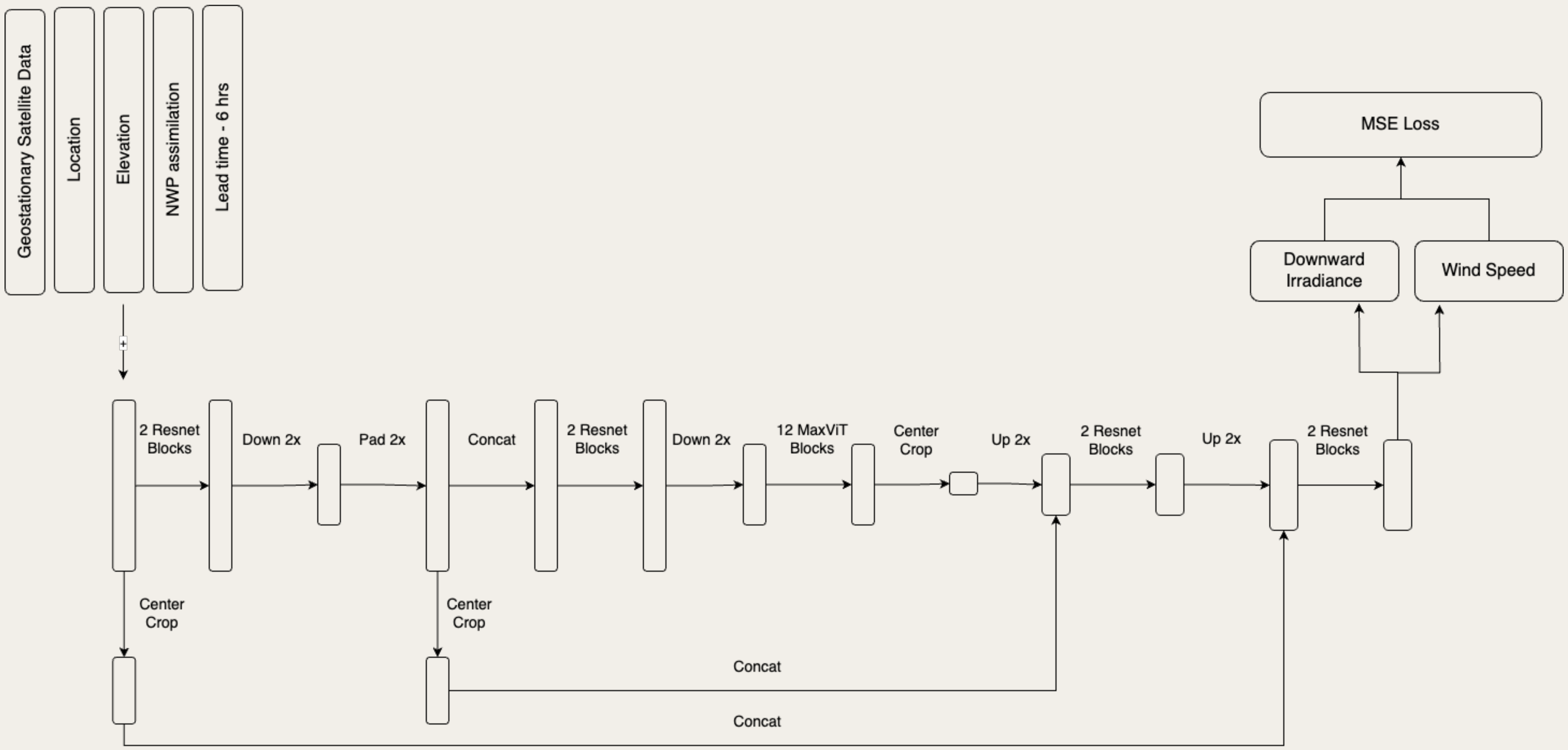


Forecasting Task Architecture - Detailed



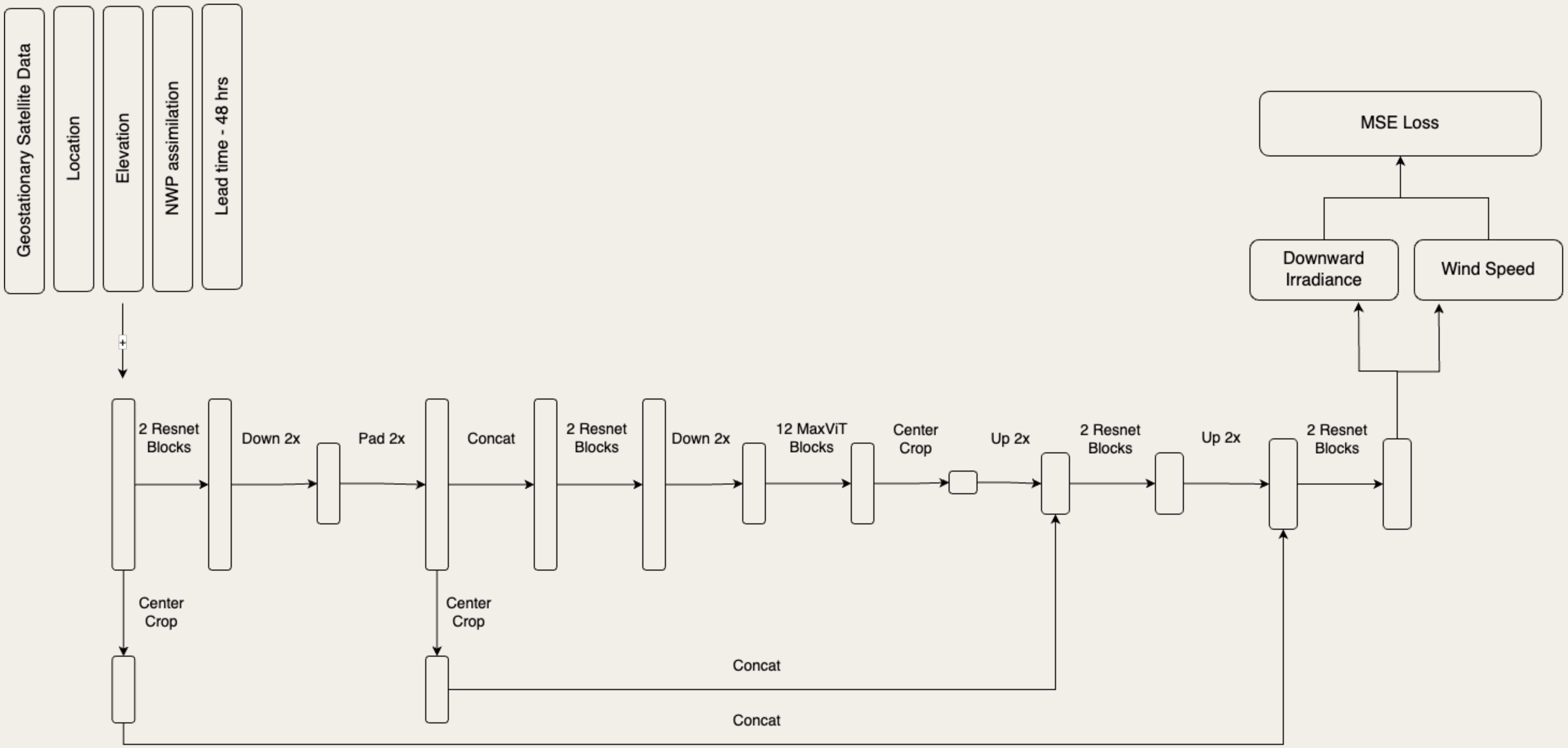
reint.ai

AI weather model – Intra-day

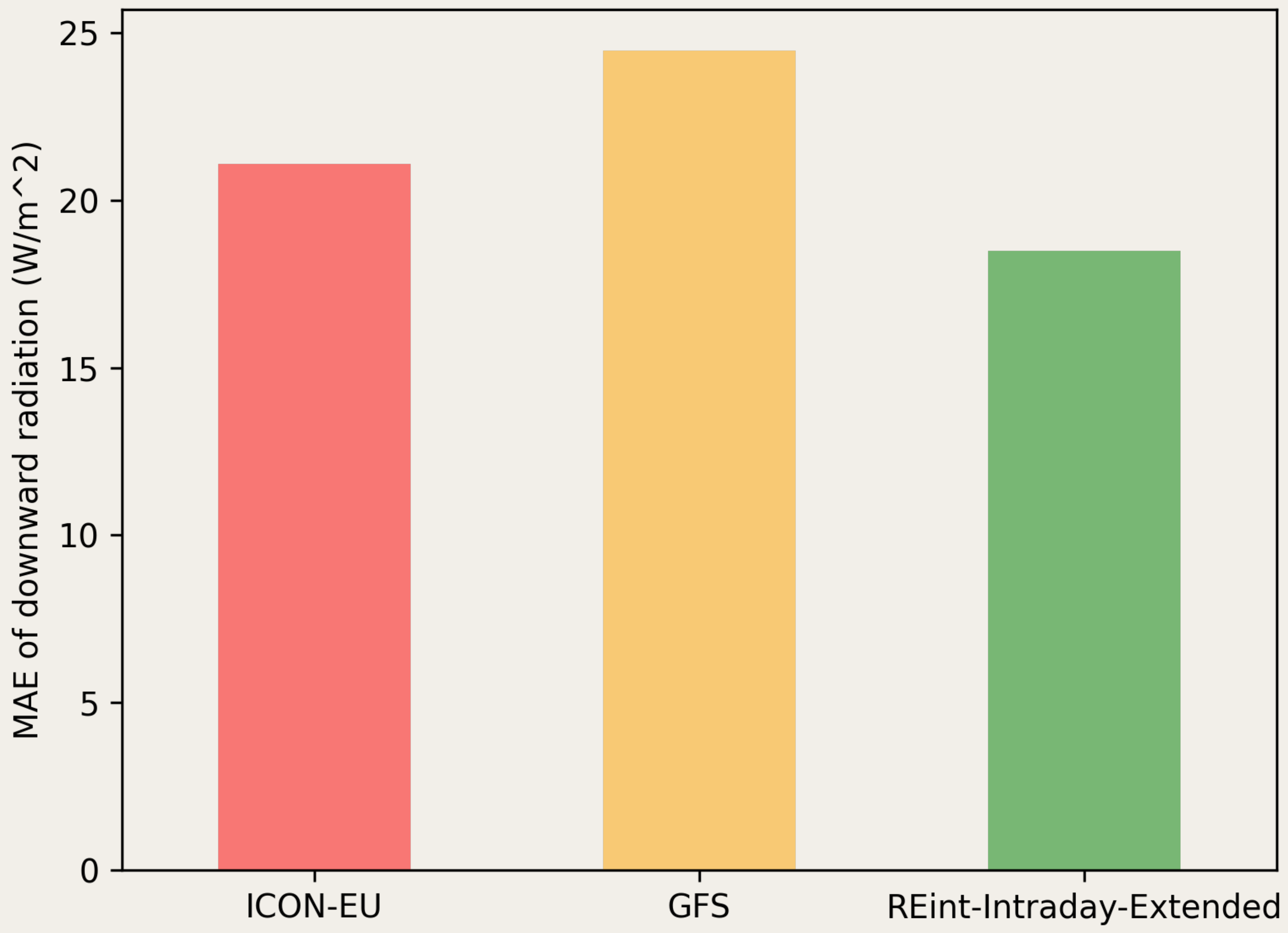


Deep Learning for Day Forecasts from Sparse Observations arXiv:2306.06079v3

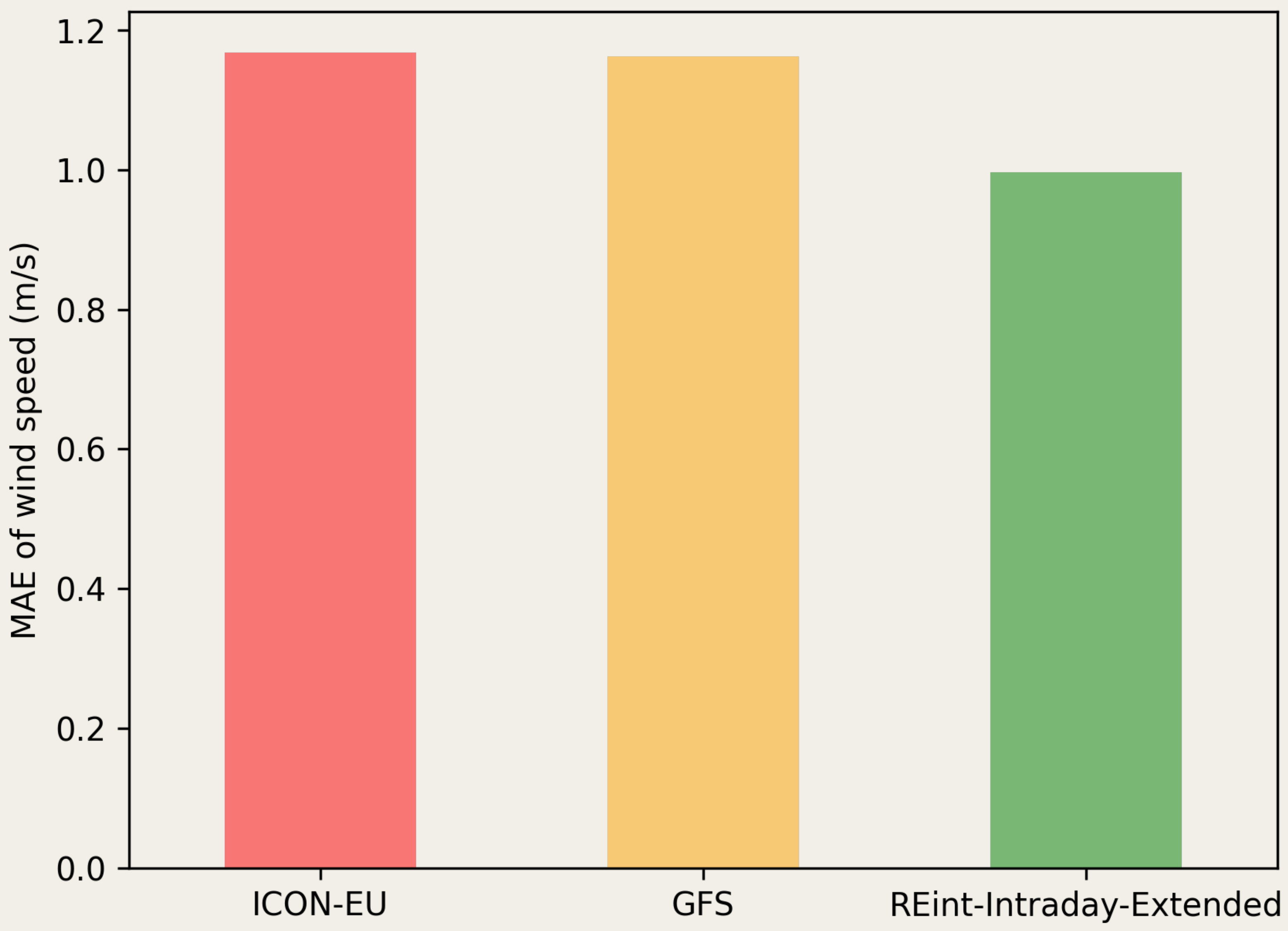
AI weather model – Extended for day-ahead



AI weather models - Performance



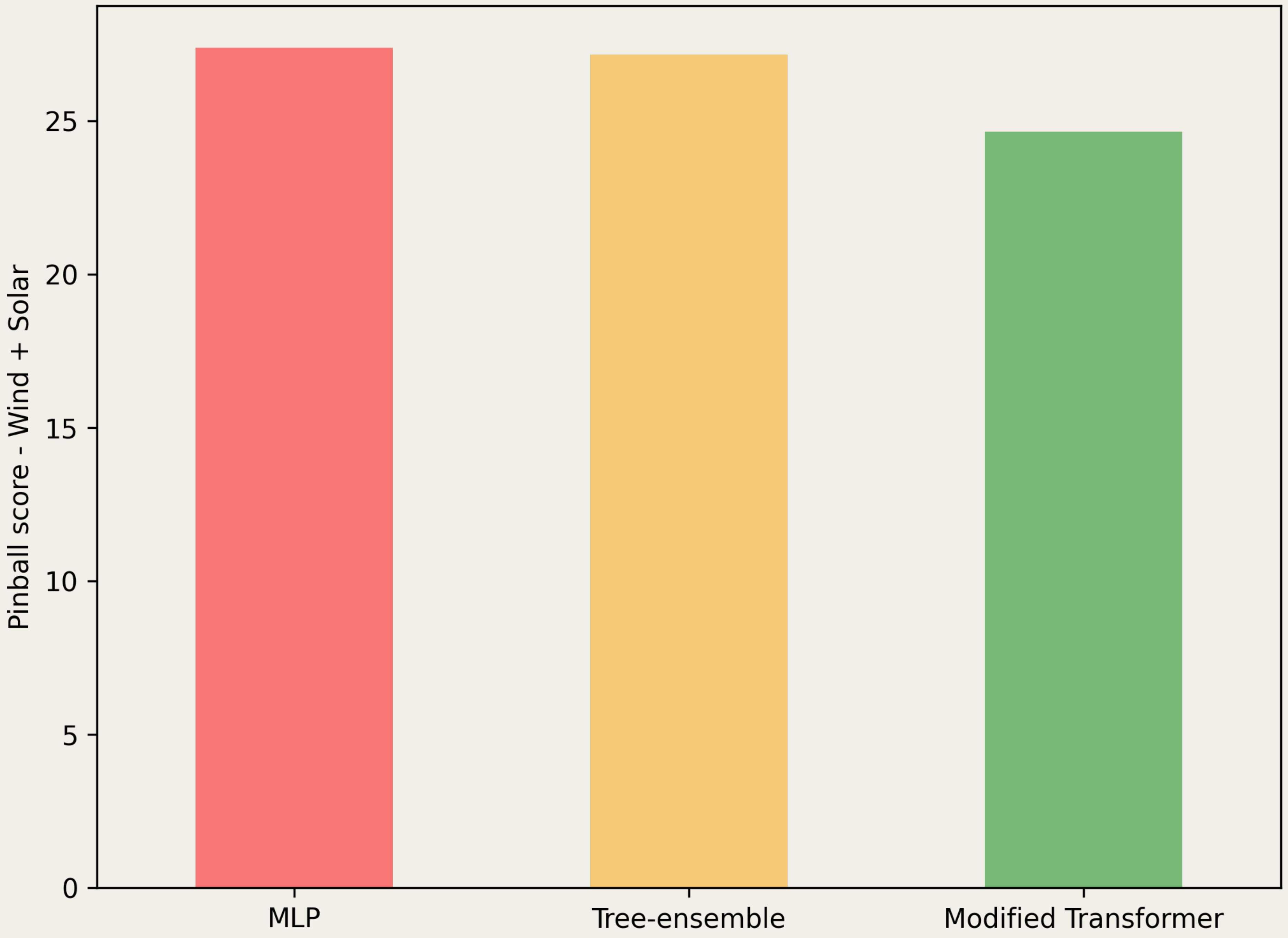
Downward Irradiance



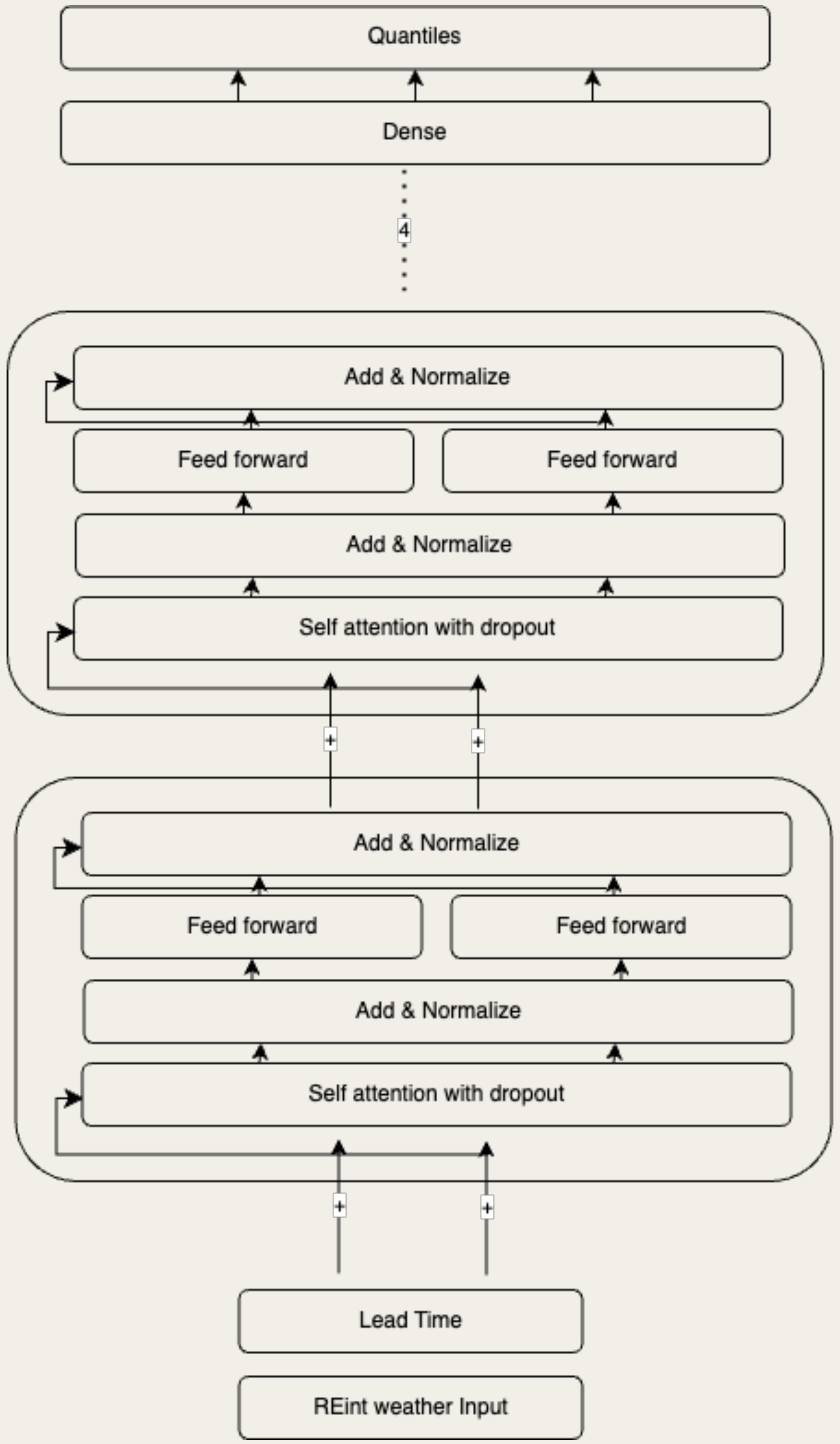
Wind Speed

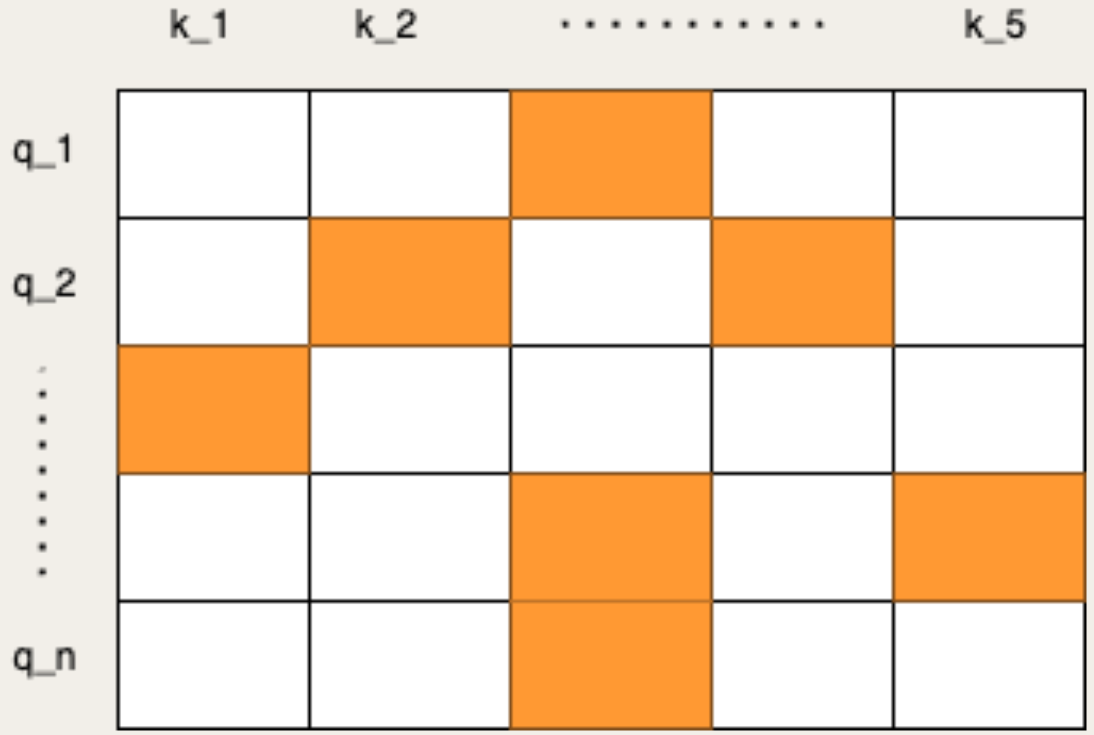
reint.ai

Weather to power



Weather to power





Elemental Dropout

Final Set Up for forecasting

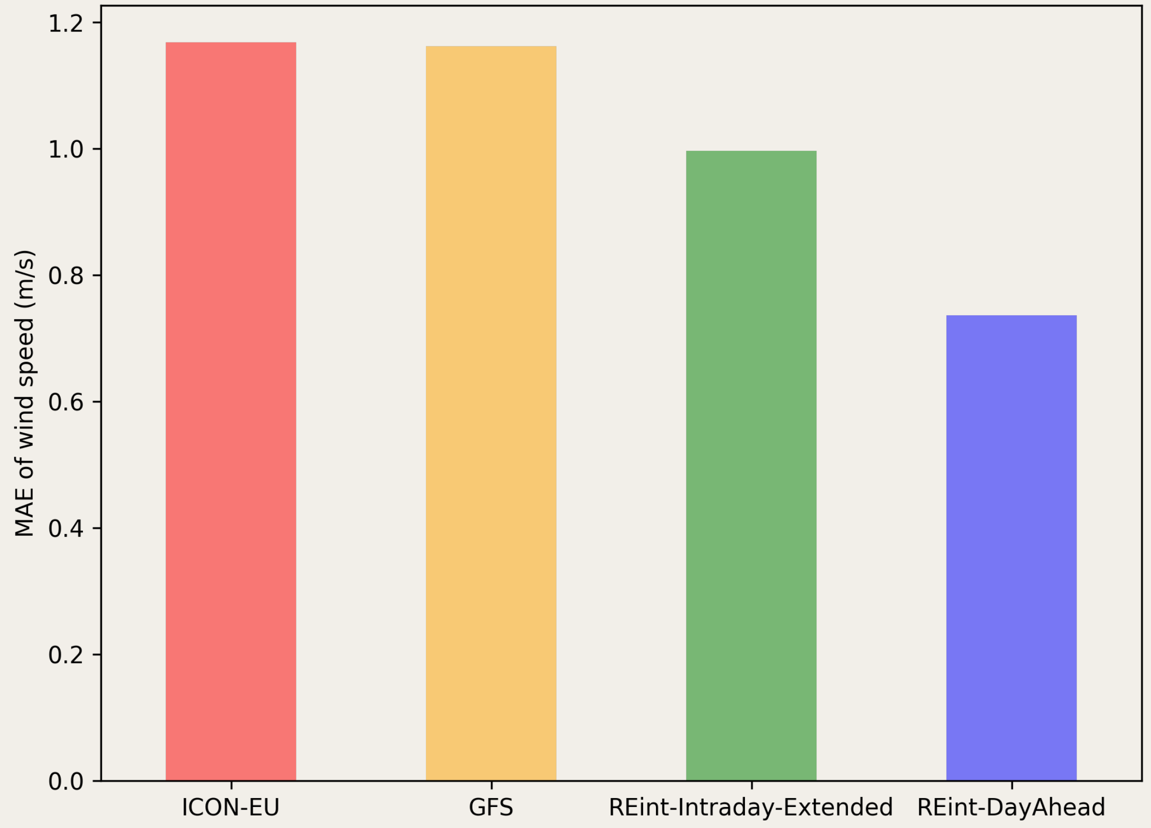
- Extend REint's Intra-day AI weather model for day-head horizon
- Transformer that takes weather inputs and converts to normalized power quantiles
- Sort the quantiles
- Update capacity (based on REMIT) in post-processing
- Final result - pinball score 24.64

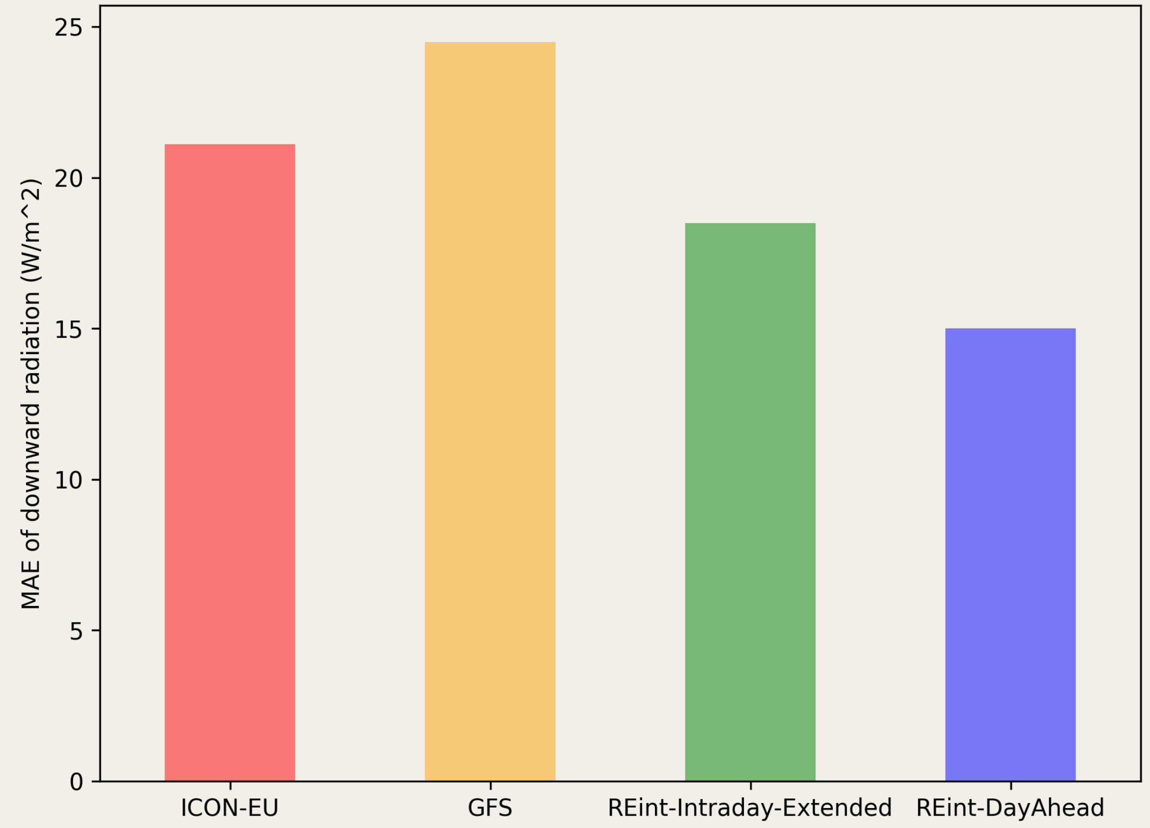
Set Up for Trading

- Extrapolate Solar and Wind forecasts to national level
- Demand Prediction model using NGESO demand forecast and extrapolated Solar forecast
- Use them as features to predict Day ahead Price, Imbalance Price and compute optimal bid
- Final bid is 0.5 (q50) + 0.5 (Optimal Bid)
- Result in trading – GBP 88.29M

Next Steps and Future Improvements

- Publish a detailed technical report
- Train AI weather models on more history, and higher resolution
- Incorporate NWP future state into the power forecasting models
- More weather variables for the downstream models
- National level models for trading task





reint.ai

SVENSKA KRAFTNÄT

Svk – HEFTcom

2024-06-26

Jon Olauson

Jon.olauson@svk.se

Olle Viotti

Olle.viotti@svk.se

Jakob Huss

Jakob.huss@svk.se

Motivations

- Learn about probabilistic forecasts
- Benchmark against global competitors
- Try new ideas
- Learn from competitors solutions

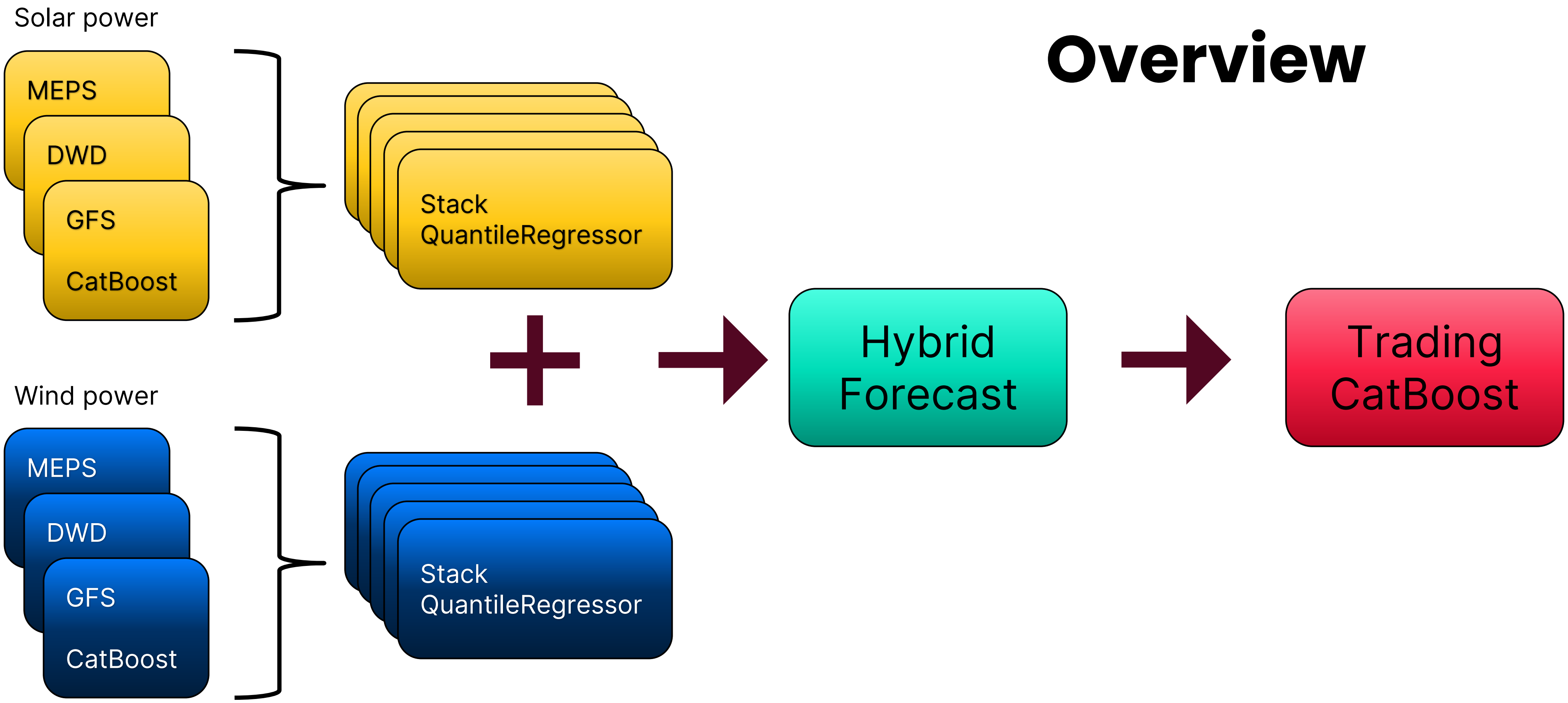
Goals

- High availablility
- Low errors
- Focus on the forecasting track
- Develop new forecasts quickly

SVENSKA KRAFTNÄT

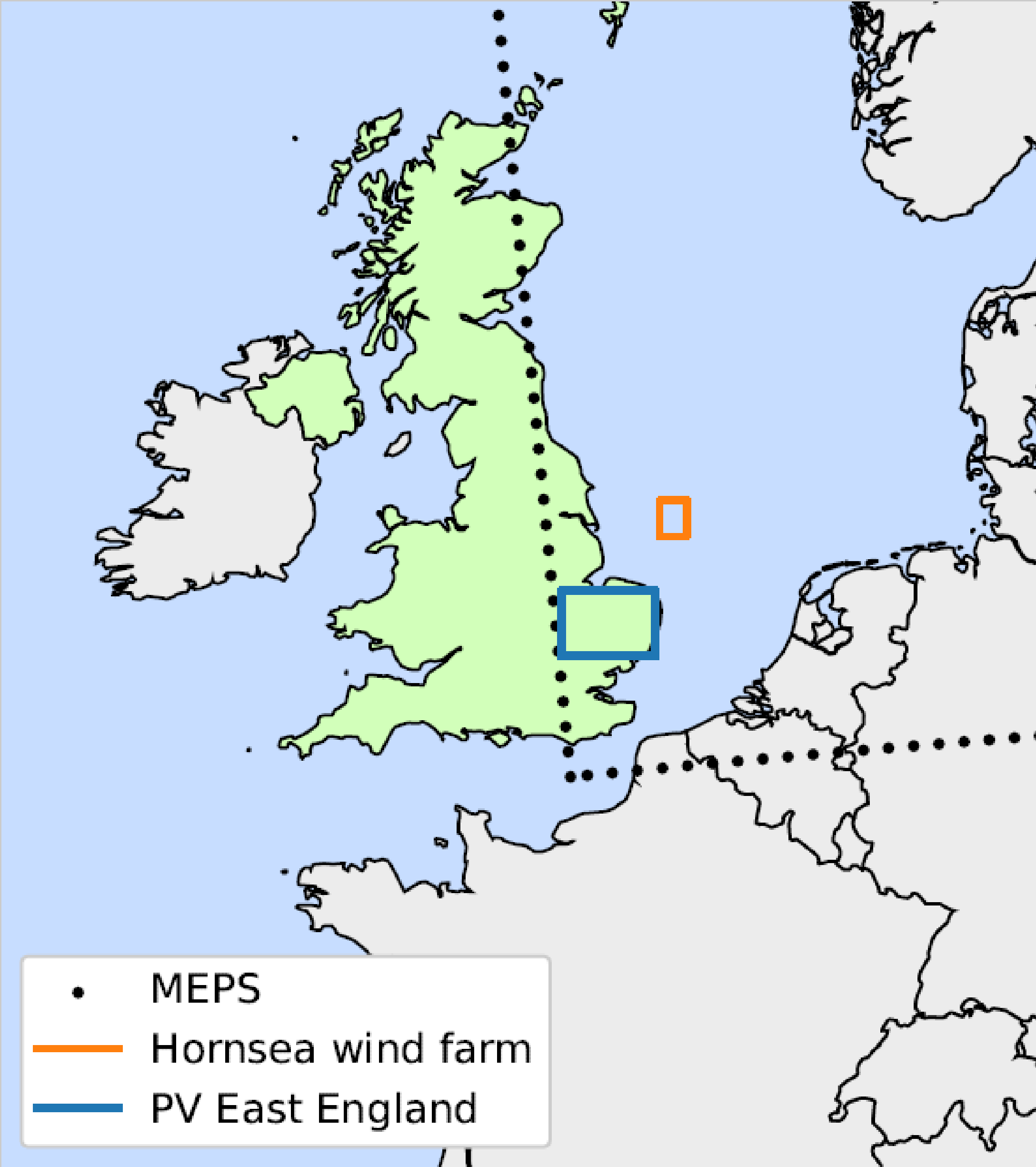
Stack of cats

Overview


Solar power
MEPS
DWD
GFS
CatBoost
Stack
QuantileRegressor
Wind power
MEPS
DWD
GFS
CatBoost
Stack
QuantileRegressor
Hybrid
Forecast
Trading
CatBoost

Weather data

- GFS – provided in competition
- DWD – provided in competition
- **MEPS** – provided by met.no



Data – Wind power

Weather features

- Wind speed
- Wind direction
- Temperature
- Air pressure
- Relative humidity

Feature engineering

- (Weather features).diff()
- Wind speed lags
  [-2, -1, 0, 1, 2]
- sin(Wind direction)
- cos(Wind direction)

Datetime features

- Sin(hour), cos(hour),
- Sin(month), cos(month)
- Minute, year

Target

- Wind power

Data – Solar power

Weather features

- Radiation
- Cloud cover
- Temperature

Hornsea area features

Hornsea weather – same weather model

Feature engineering

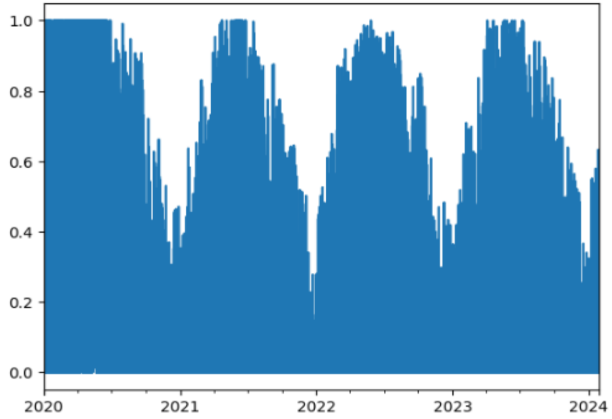
- (Weather features).diff()
- Weather features lags [-2, -1, 0, 1, 2]

Datetime features

- Sin(hour), cos(hour),
- Sin(month), cos(month)
- Minute, year

Target

- Solar power / cumulative maximum solar power per hour of day [0, 1]



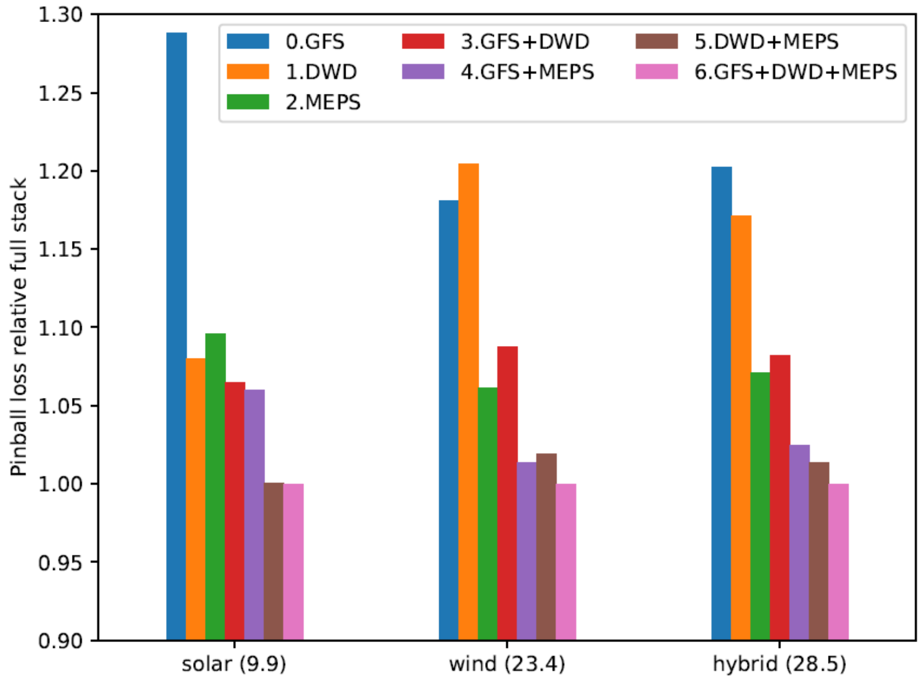
Solar and wind power models

CatBoost

- One model for each weather data set
- Drop rows with nan's
- Using MultiQuantile Loss
- Reverse cumulative division target (solar)

Stack quantile

- Fill nan's with predictions from other CatBoost models
- All CatBoost quantiles as input
- QuantileRegressor for each quantile
- Sort the quantiles
- Clip output [0, 1000] (solar)
- Clip output [0, REMIT] (wind)



Hybrid results

Test year 2023

- 28.5 Pinball loss
- 8% improvement with MEPS

  (Pink vs Red)

During competition

- 22.18 Pinball loss

Trading strategy

Features

- Hybrid forecast
- (DA_Price – SS_Price)
  .groupby((hour, minute))
  .mean()

Datetime features

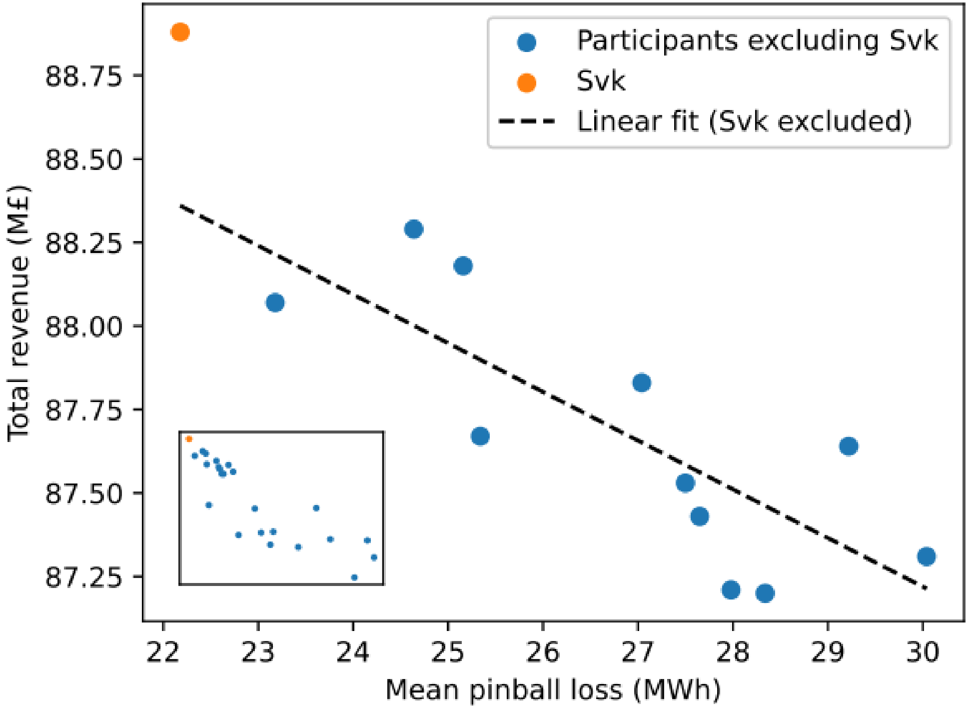
- Sin(hour), cos(hour),
- Sin(month), cos(month)
- Minute, year

Model

- CatBoost
- MAE loss
- Drop outliers on DA_Price above 300 during training
- 0.2 * q50_hybrid_forecast + 0.8 * Trading model output

Target

- Historic optimal bid



Trading results

Test year 2023

- 0.9% better than using q50 prediction

During competition

- 0.6% better than trend line for top performers excluding Svk
- 88.88 M£

Robustness

Good ideas

- Retry all http requests
- Multiple weather data sources in separate models
- Fill nan’s with available predictions before stacking (100% submissions)
- Try next model -> Try … Except …
- Email notifications of new REMIT messages

Not so good ideas

- Manual limit of wind power output based on REMIT
  - Human error caused large errors in beginning of May

Questions?