上海交通大學
SHANGHAI JIAO TONG UNIVERSITY

Aggregated Probabilistic Forecasting and Stochastic Trading Strategies for HEFTCom2024

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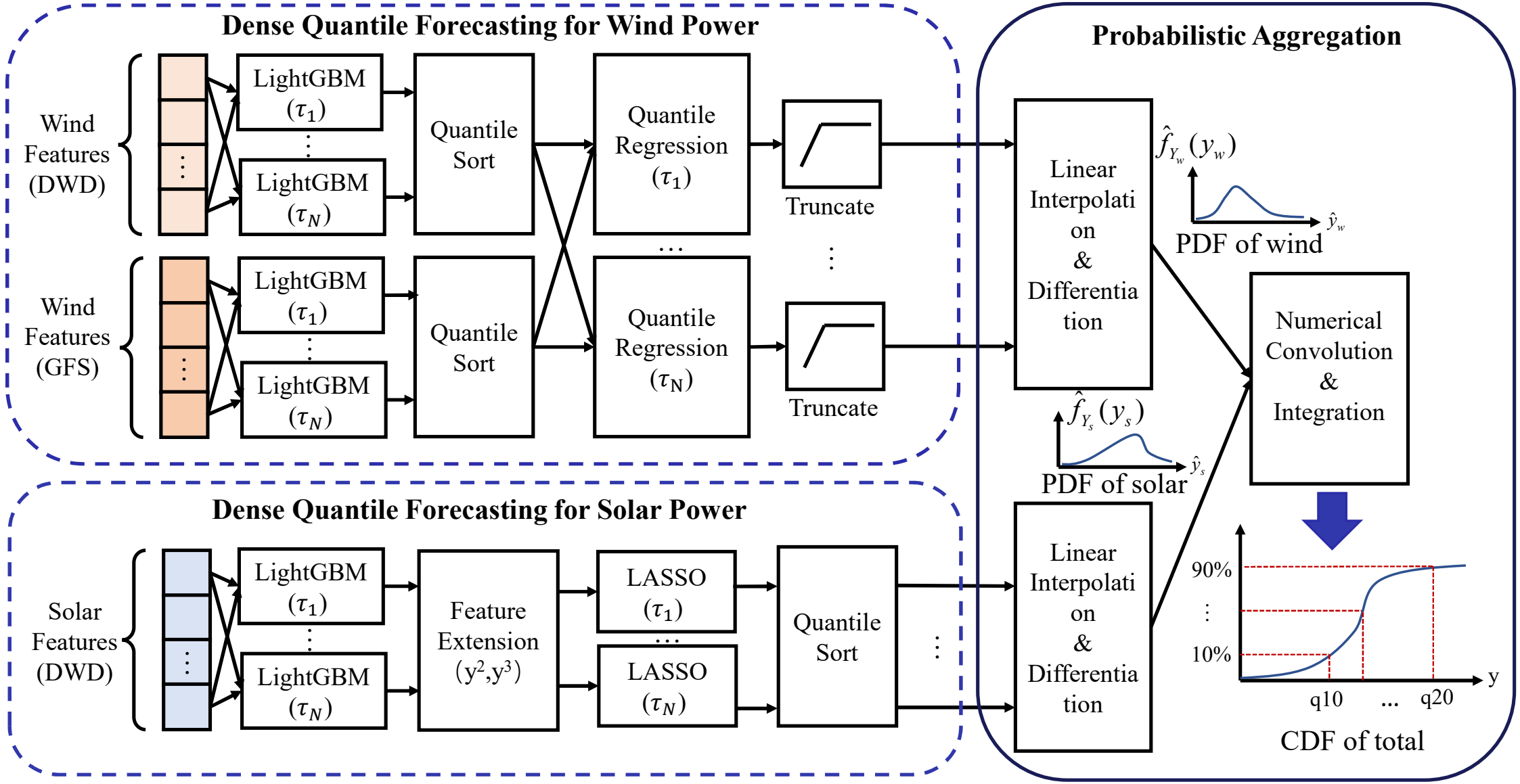
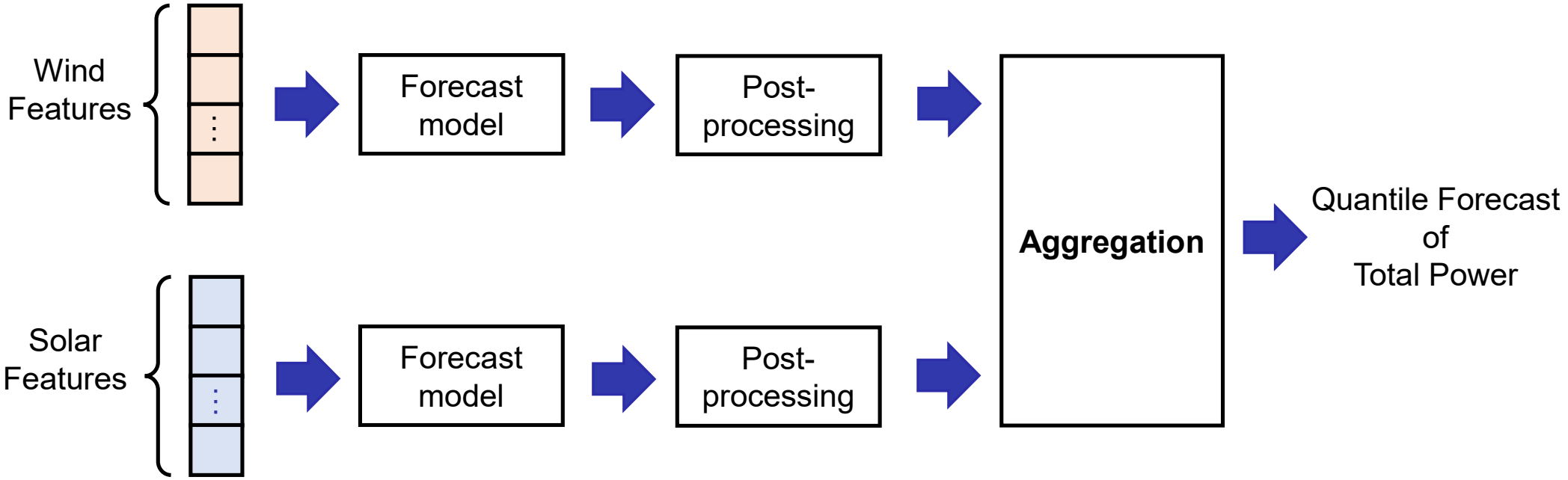
3rd in Trading Track
4th in Forecasting Track
1st in Student Teams

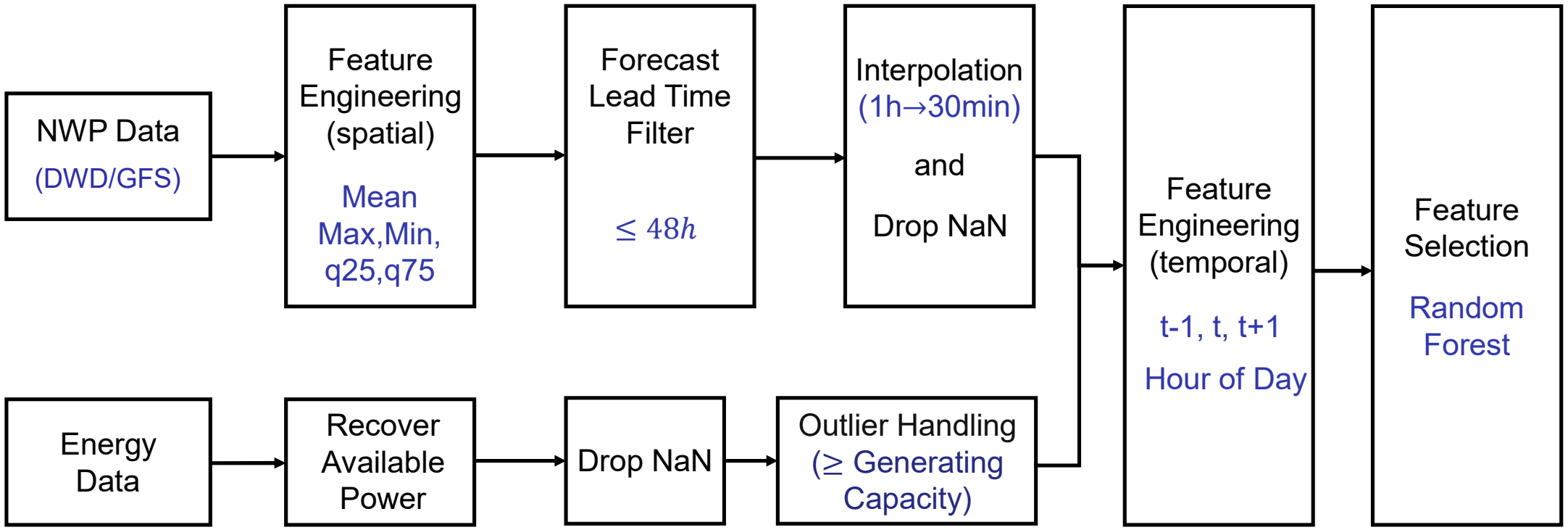
2024/11/14


Dense Quantile Forecasting for Wind Power
Wind Features (DWD)
Wind Features (GFS)
LightGBM (τ_1)
LightGBM (τ_N)
Quantile Sort
Quantile Regression (τ_1)
Quantile Regression (τ_N)
Truncate
Truncate
Probabilistic Aggregation
Linear Interpolation & Differentiation
$\hat{f}_{Y_w}(y_w)$
PDF of wind
$\hat{y}_w$
$\hat{f}_{Y_s}(y_s)$
PDF of solar
$\hat{y}_s$
Numerical Convolution & Integration
90%
10%
q10
...
q20
y
CDF of total
Dense Quantile Forecasting for Solar Power
Solar Features (DWD)
LightGBM (τ_1)
LightGBM (τ_N)
Feature Extension (y^2,y^3)
LASSO (τ_1)
LASSO (τ_N)
Quantile Sort
Linear Interpolation & Differentiation

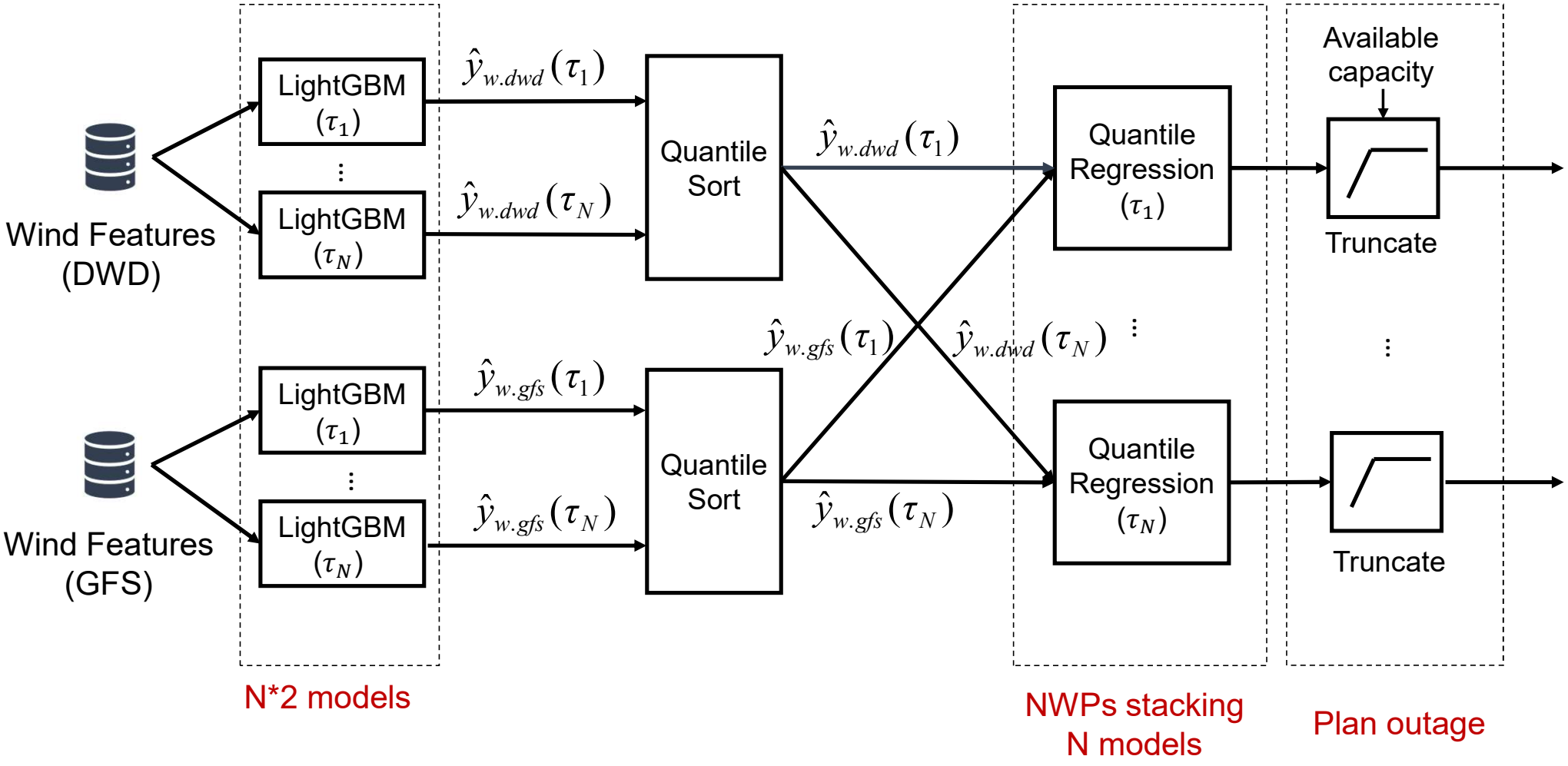
Decoupled and Aggregated Forecasting



Data Pre-processing



Forecasting Track— Quantile Forecast （Wind）

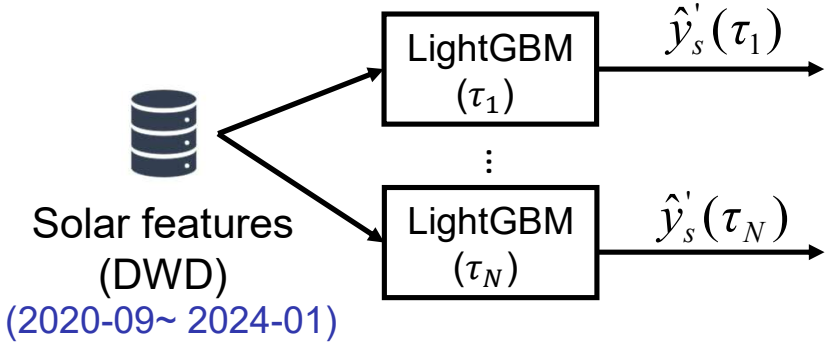


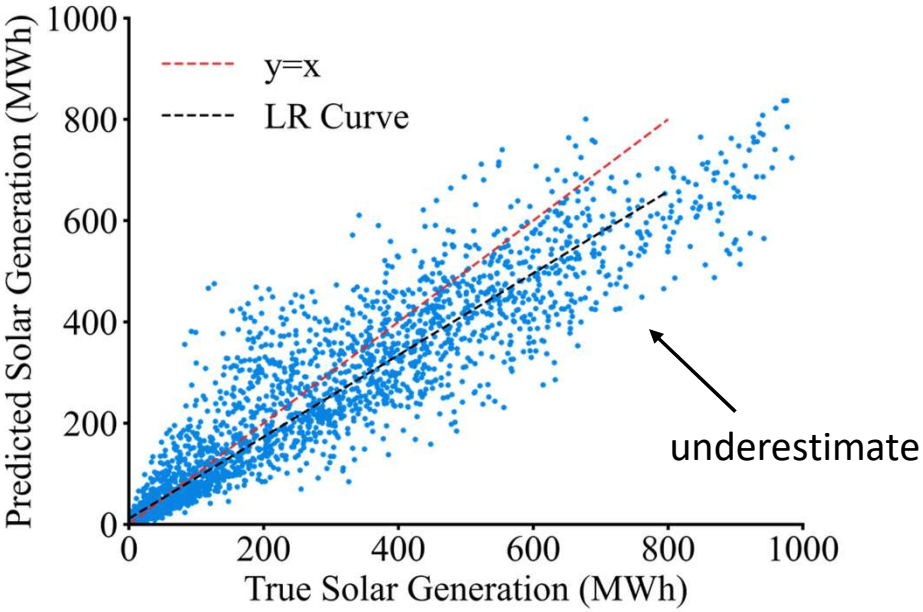
Forecasting Track— Quantile Forecast （Solar）

- Solar capacity changes after the start of HEFTcom

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

- Our original framework





Forecasting Track— Quantile Forecast （Solar）

- We consider a polynomial post-processing model:

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

Final forecast

from model trained on historical data

- Using LASSO quantile regression to post-process the forecasts from the model trained on historical data

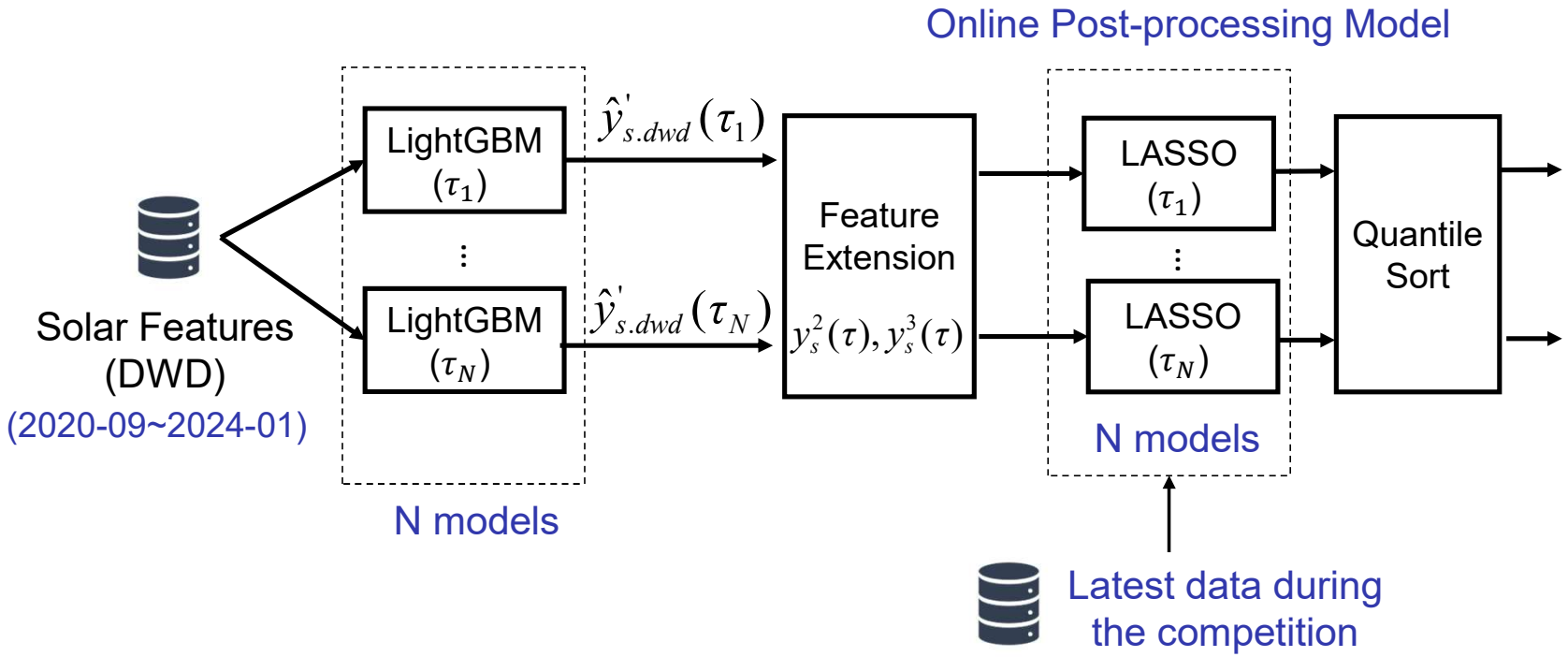
$$\min_{\boldsymbol{\beta}} L_{\tau_i}(y_s, \hat{y}_s) = \tau_i (y_s - \hat{y}_s)^+ + (1-\tau_i)(\hat{y}_s - y_s)^+ + \lambda \sum_{j=1}^{3} |\beta_j| \quad i = 1, \ldots, N$$

Actual generation after 2024-02-19

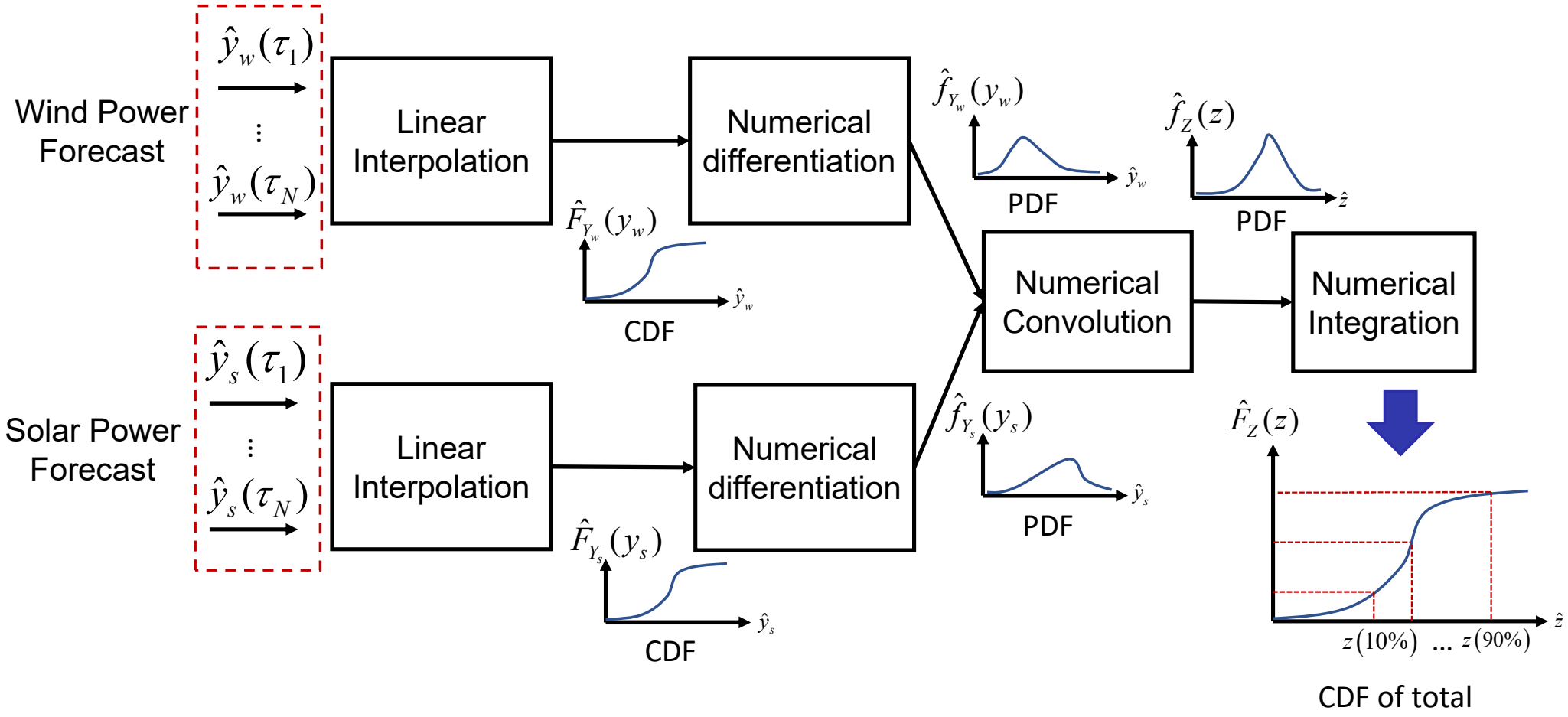
L1-regularization to make β sparser

Forecasting Track— Quantile Forecast （Solar）

- Revised framework:



Forecasting Track— Quantile Aggregation



Forecasting Track— Hyperparameter Tunning

- Optuna Framework
- Search q50 wind and solar model only

```
def objective(trial,X,y,quantile):

    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
        }
```

Trading Track— Rules

- The revenue:

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

Day-ahead market revenue | Imbalance revenue | Penalty of generation deviation

- We define the price difference:

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

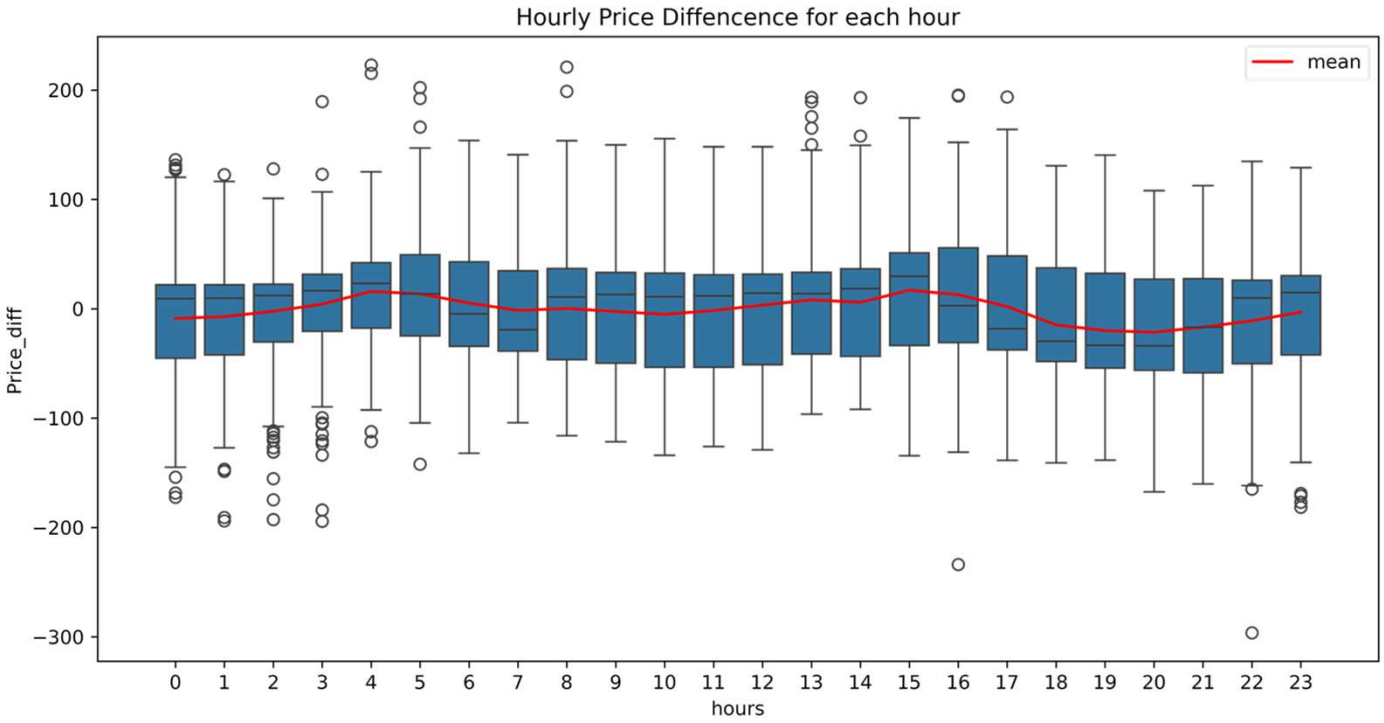
$$F(\hat{z}_b) = \pi_{ss} z + \pi_d \hat{z}_b - 0.07(z - \hat{z}_b)^2$$

constant | Needs to maximize

Notation

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

Trading Track— Difficulty of Price Forecast



Why price forecasting is difficult ?

- Price difference updates are delayed by 4-5 days
- Lack of global information about the market
- Very high variance caused by power imbalance

What can we find?

- Statistically, the price difference is related to the hour of day.

Trading Track— Stochastic Trading

- Probabilistic modeling of uncertain price difference with hour *t* as a covariate
- We optimize the expectations of trading revenue:

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

- The optimal solution 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

power forecast

Trading Track— Decision Loss

- Considering the optimal decision:

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

- The actual revenue under actual generation and price difference:

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

- The theoretical optimal revenue (if forecast=actual):

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

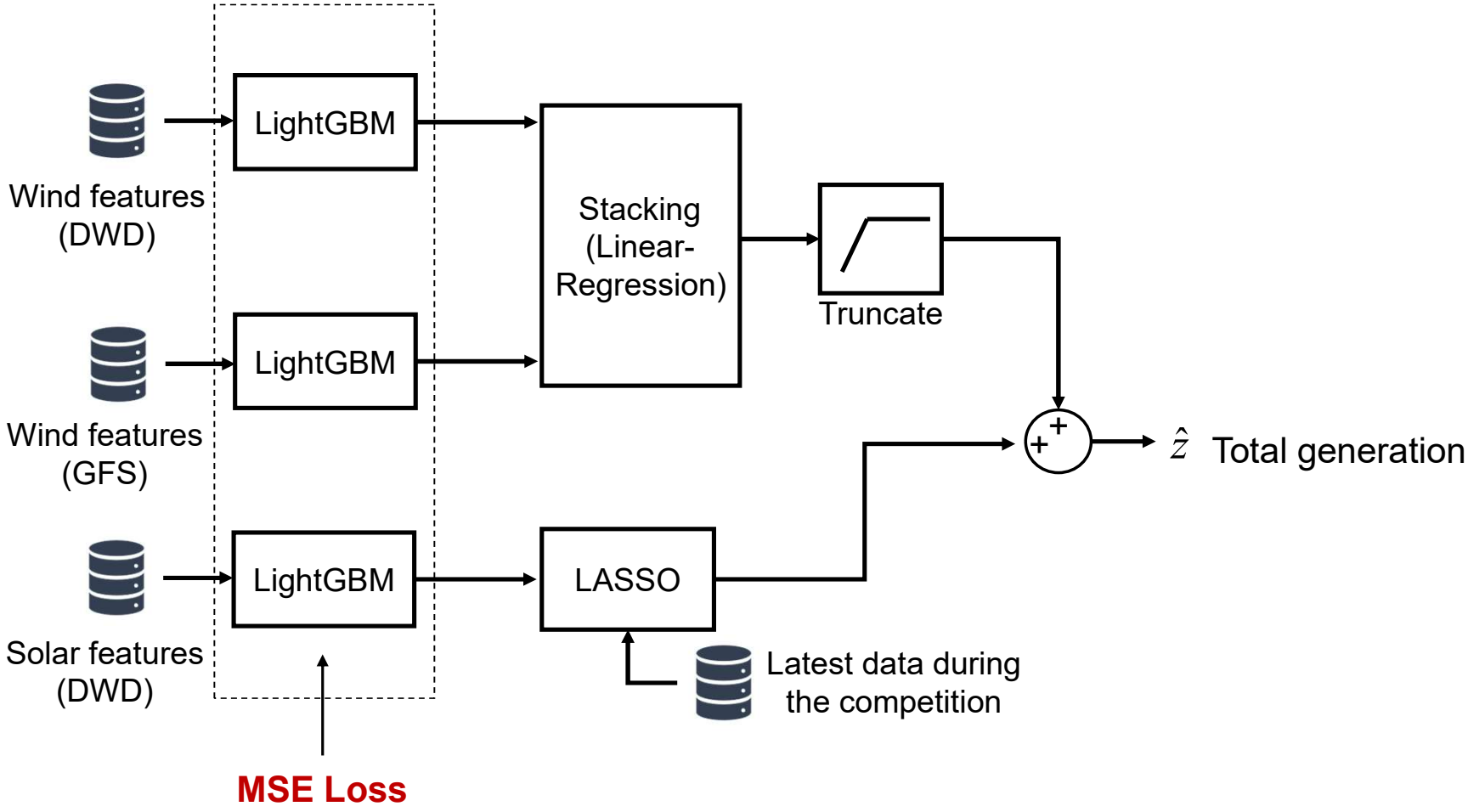
where $z_b^* = z + 7.14\pi_d$

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

$$F(z_b^*) - F(\hat{z}_b^*) = 0.07(z - \hat{z})^2 + 3.57(\pi_d - \hat{\pi}_d)^2 + (z - \hat{z})(\pi_d - \hat{\pi}_d)$$

Decision loss | MSE | MSE | Coupled term

Trading Track— Point Power Forecasting for Trading



Key Approaches to The Specific Challenge of HEFTCom

- **Stacking models with different NWPs**

  Motivation: To reduce the variance in wind power forecasting

- **Aggregated Quantile Forecasting**

  Motivation: Theoretically optimal aggregated method

- **Online Solar Post-processing model**

  Motivation: Increased solar capacity without enough new data

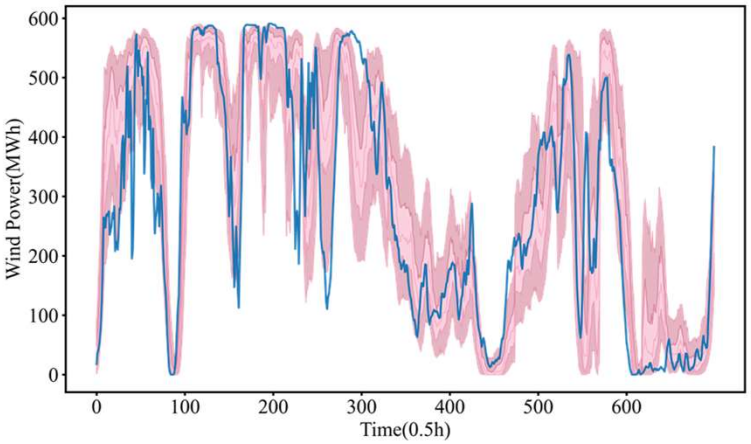
- **Stochastic Trading Strategy**

  Motivation: To improve the trading revenue considering the uncertainty of price difference; prices is hard to predicted but statistically related to time series features; we can optimize the long-term expectation

Summary: Effective Approaches

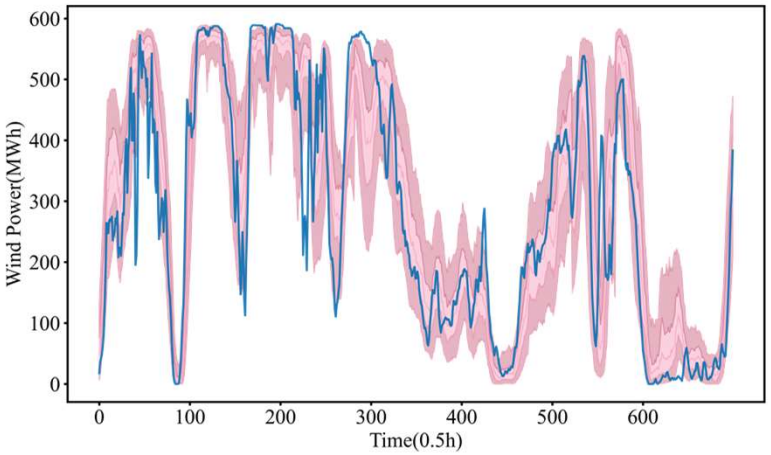
- **Stacking models with different NWPs**
  - Test period: 2023-02-01~2023-08-01, ref_time=00:00, 23≤valid_time-ref_time ≤48
  - Training dataset: exclude test period

Only DWD data



(Partly data displayed)

Ensembled weather



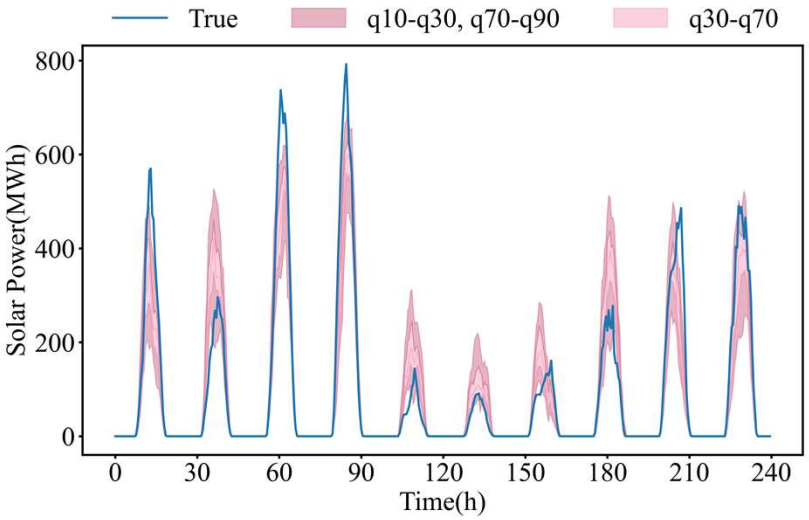
(Partly data displayed)

Mean pinball loss (all quantiles): 28.97

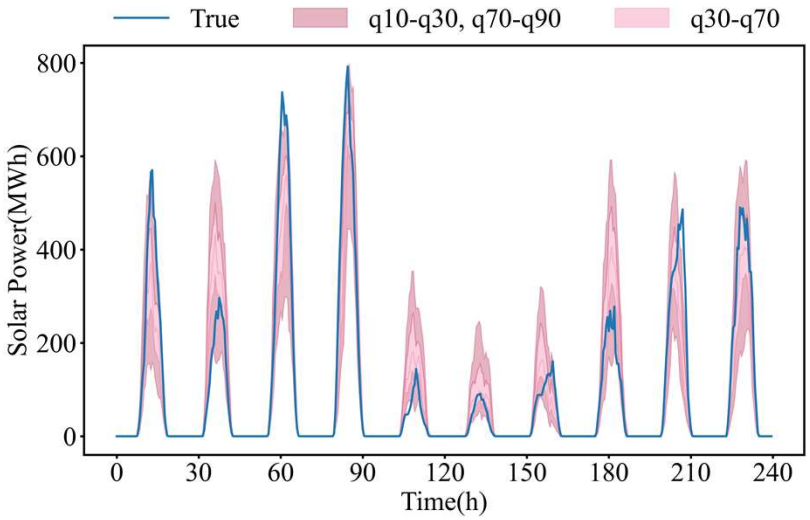
Mean pinball loss (all quantiles): **27.13**

Summary: Effective Approaches

- **Online Post-processing Model**
  - Latest solar data: 2024-02~2024-05 (dwd only)
  - Training set : testing set = 6:4 (random spilit)



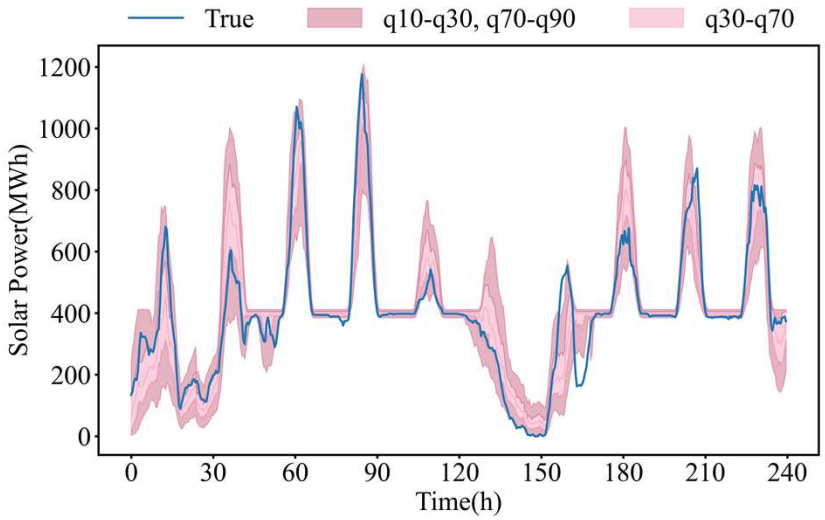
Mean pinball loss: 15.25



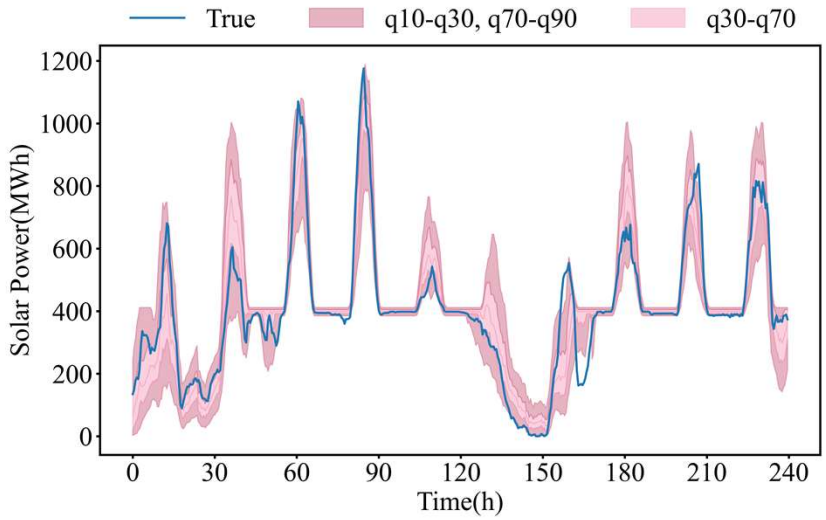
Mean pinball loss: **13.62**

Summary: Effective Approaches

- **Quantile Aggregation**
  - Test period: 2024-02-020~2024-05-19, ref_time=00:00, 23≤valid_time-ref_time ≤48
  - Training dataset: exclude test period



Mean pinball loss: 24.41



Mean pinball loss: **24.21**

Summary: Effective Approaches

Stochastic Trading

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

Results

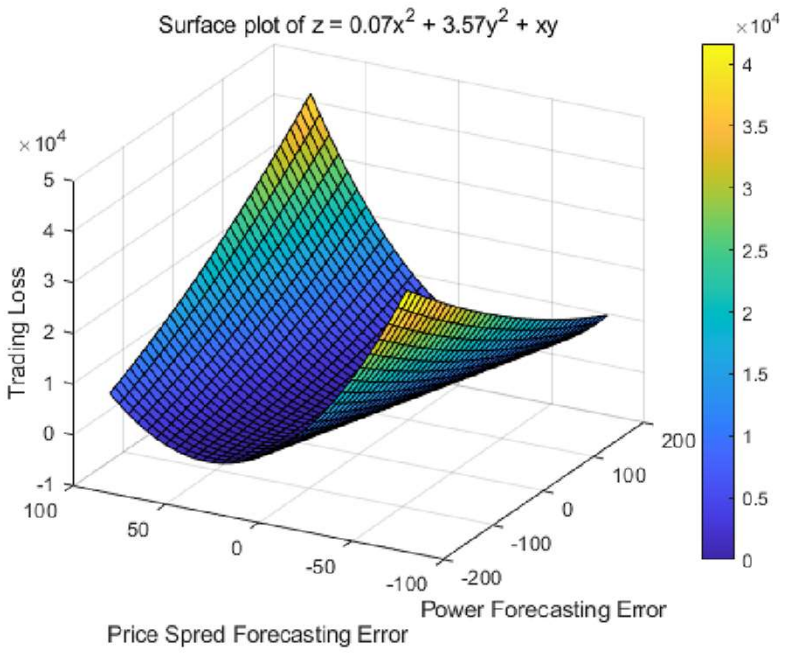
Methods	MAE	RMSE	Mean Daily Revenue (EUR)	Improvement
$\hat{z}_b^* = \hat{z}(q50)$	87.0	130.4	1711694.5	/
$\hat{z}_b^* = \hat{z}(MSE)$	89.0	128.6	1713914.7	0.13%
$\hat{z}_{b,t}^* = \hat{z}_t(q50) + 7.14\bar{\pi}_{d,t}$	/	/	1718821.93	0.42%
$\hat{z}_{b,t}^* = \hat{z}_t(MSE) + 7.14\bar{\pi}_{d,t}$	/	/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

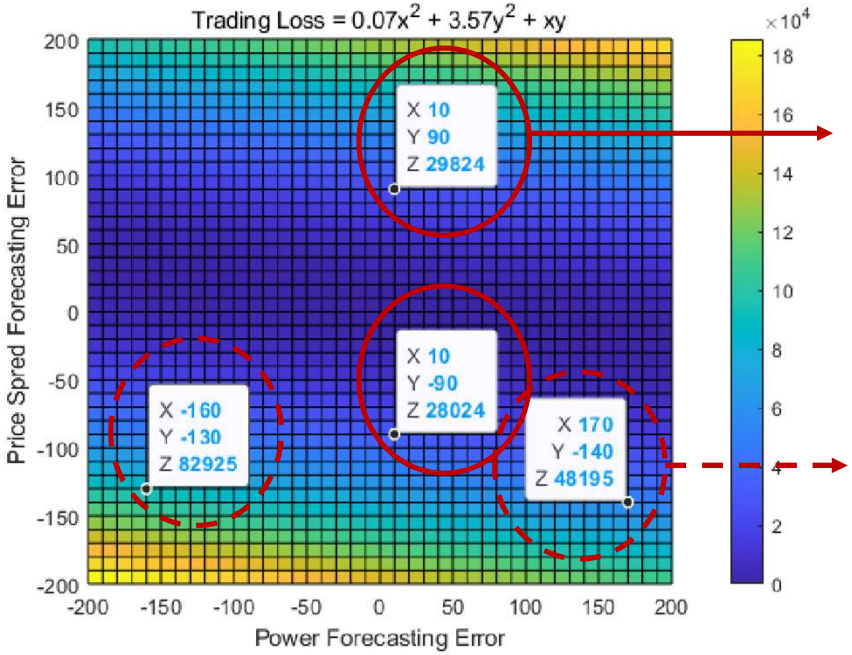
Our Further Work

- The decision loss

$$F(z_b^*) - F(\hat{z}_b^*) = 0.07\left(z - \hat{z}\right)^2 + 3.57(\pi_d - \hat{\pi}_d)^2 + (z - \hat{z})(\pi_d - \hat{\pi}_d)$$

- Asymmetric impact of forecast errors on downstream revenue

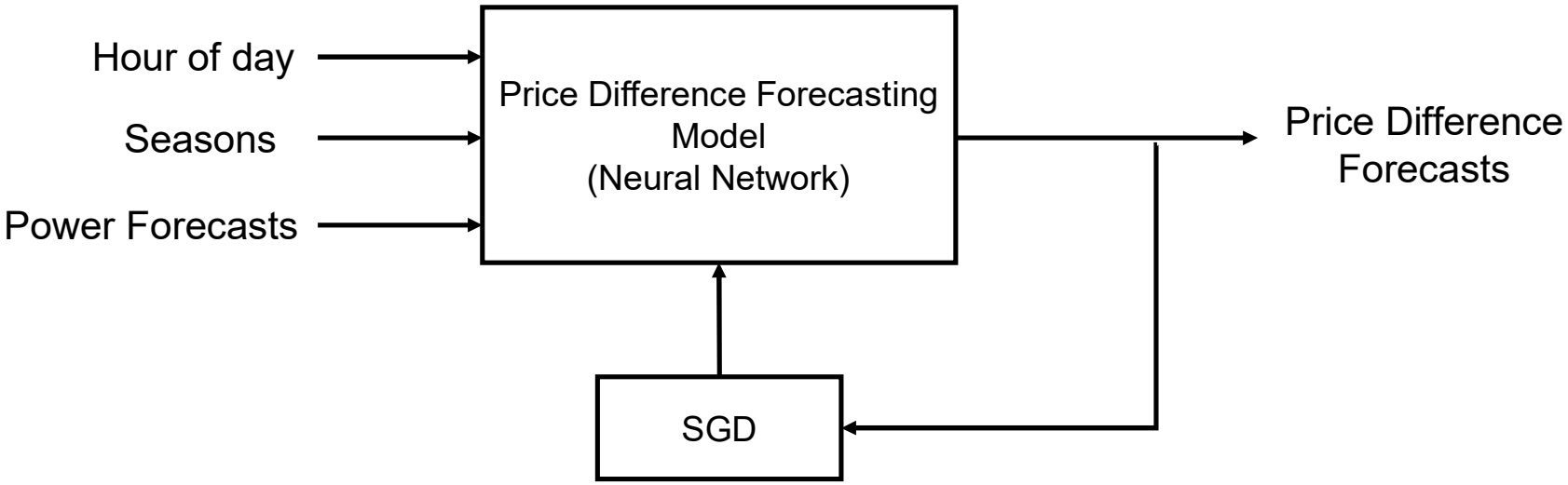




- Same accuracy may lead to different revenue
- high accuracy may lead to high revenue loss

Our Further Work

- 1. Value-oriented Forecasting



minimize $F(z_b^*) - F(\hat{z}_b^*) = 0.07\left(z - \hat{z}\right)^2 + 3.57(\pi_d - \hat{\pi}_d)^2 + (z - \hat{z})(\pi_d - \hat{\pi}_d)$

- 2. Trading with deterministic price difference and power forecasts

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14 contributions in the last year — Contribution settings

2024
2023
2022

THANKS!

The paper and code is coming soon