Joint University Student Exchange Program

Design of a Quantile Regression Forecasting-based Robust EMS for Large-Scale Loads

Seonggyeol Kim · Yubin Lee
Future Power Network And Economics Lab. Chungbuk National University

충북대학교
CHUNGBUK NATIONAL UNIVERSITY

Contents

1. Background

01. Background

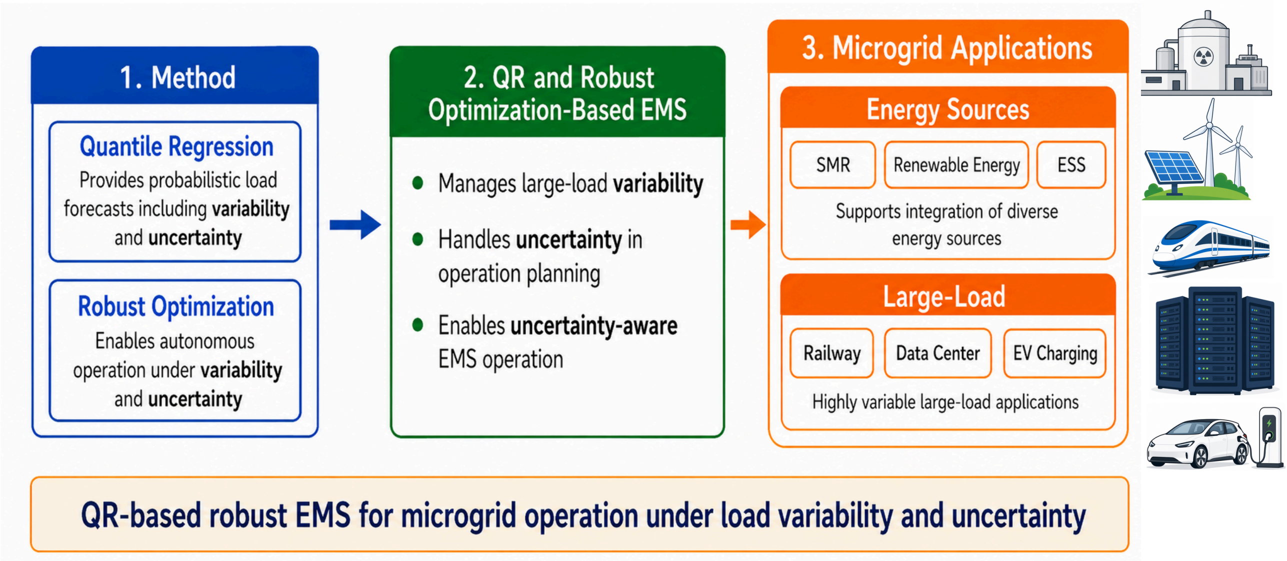
■ Background

- Rapid growth of large-scale loads, such as data centers and EV charging infrastructure
- Concern over increased load variability risk due to large-scale load growth
- Need for distributed energy production and consumption near major load centers
- Necessity of a robust EMS for reliable operation under load variability

01. Background

■ Research's Goal

- Design of a QR(Quantile Regression) based robust EMS for managing variability and uncertainty of large–scale loads



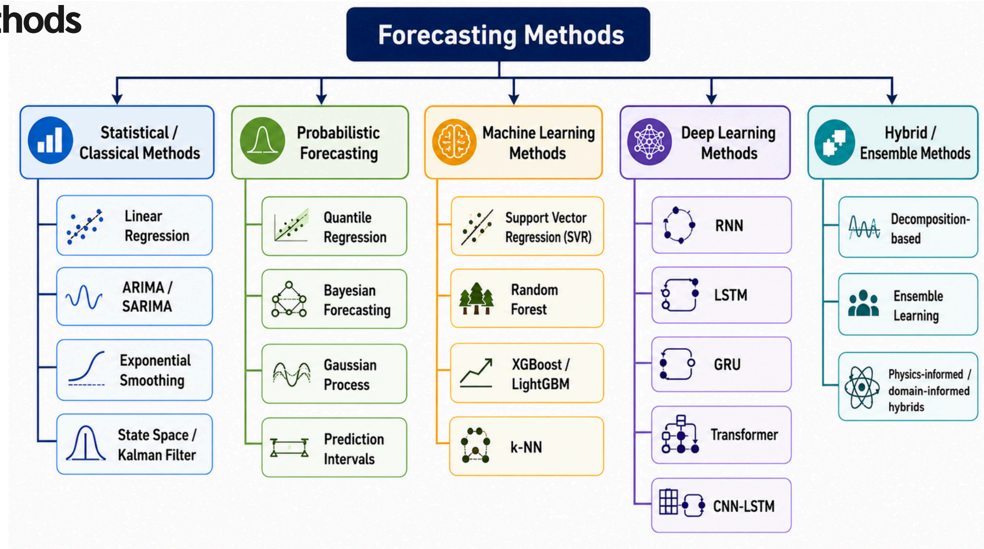
2. Quantile Regression

02. Quantile Regression

■ Importance of Forecasting Methods

- Growing importance of load forecasting with increasing load variability
- Provision of key input data for EMS operation and optimization under uncertainty

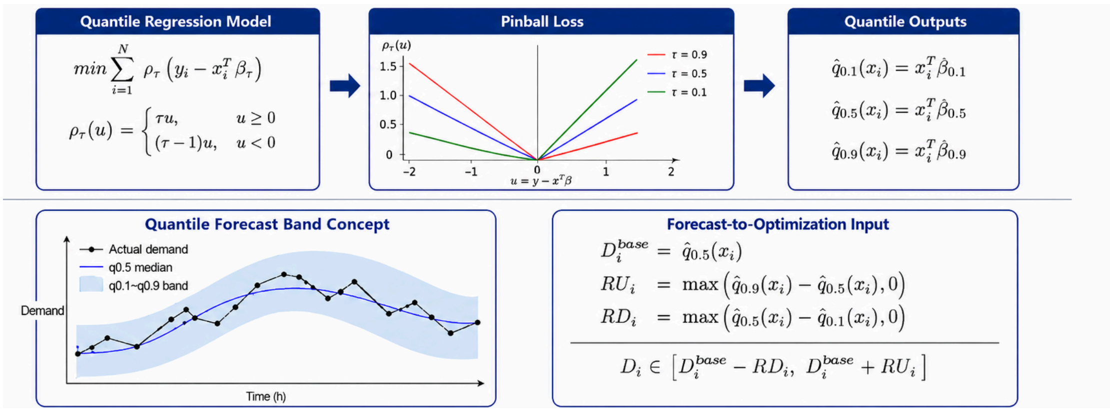
■ Various Forecasting Methods



■ Quantile Regression

- Point forcasting : Single expected value → Limited uncertainty representation
- Quantile Regression : Conditional quantile estimation → Genration of prediction band

→ **Selection rationale** : Explicit representation of variability and forecasting uncertainty



Derivation of reserve requirements from quantile prediction bands

※ reserve : Standby capacity margin defined by the spread between median and boundary quantiles

02. Quantile Regression

■ Forecast Evaluation

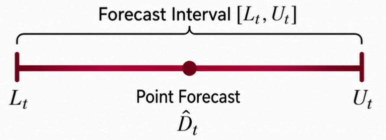
Metric	Formula	Interpretation
PICP	$PICP = \frac{1}{N}\sum_{i=1}^{N} \varepsilon_i \qquad \varepsilon_i = \begin{cases} 1, & if\ \ y_i \in [L_i, U_i]; \\ 0, & if\ \ y_i \notin [L_i, U_i]. \end{cases}$	**Meaning** : Coverage probability **Desirable property** : Close to the nominal confidence level
PINAW	$\mathrm{PINAW} = \frac{1}{m(\max(y_{ij}) - \min(y_{ij}))}\sum_{i=1}^{m}(\mathrm{UL}_{ij} - \mathrm{LL}_{ij}), j = 1, \ldots, k.$	**Meaning** : Normalized width of the prediction interval **Desirable property** : Minimum value
PINAD	$\mathrm{PINAD} = \frac{1}{m}\sum_{i=1}^{m}\frac{D_{ij}}{\max(y_{ij}) - \min(y_{ij}}\ D_{ij} = \begin{cases} \mathrm{LL}_{ij} - y_{ji}, & \text{if } y_{ji} < \mathrm{LL}_{ij}, \\ 0, & \text{if } \mathrm{LL}_{ij} \le y_{ji} \le \mathrm{UL}_{ij}. \\ y_{ji} - UL_{ij}, & \text{if } y_{ji} > \mathrm{UL}_{ij}. \end{cases}$	**Meaning** : Magnitude of deviation outside the prediction interval **Desirable property** : Minimum value, ideally close to zero
Winkler Score	$WS = \begin{cases} D_t, & L_t \le y_t \le U_t \\ D_t + \frac{2(L_t - y_t)}{\alpha}, & y_t < L_t \\ D_t + \frac{2(y_t - U_t)}{\alpha}, & y_t > U_t \end{cases}$	**Meaning** : Overall score for interval forecast quality **Desirable property** : Minimum value

3. Robust Optimization

03. Robust Optimization

■ What is Robust Optimization

- Derivation of feasible operational solutions via uncertainty sets under demand and power generation uncertainty
- Consideration of quantile-based prediction bands instead of reliance on a single point forecast



Plan must remain feasible for all demand values within the interval.

$D_t \in [L_t, U_t]$

Objective: Minimize cost while maintaining stable operation for all load demand values within the forecast interval.

■ Why is it needed?

Point forecast only → Unexpected load demand / power generation change → Insufficient reserve / operation risk

Robust optimization → Reserve secured within interval → Stable EMS operation

1 Railway Station

Train schedules, HVAC, passenger flow, and station facilities cause rapid load fluctuations.

Robust optimization helps ensure reserve against unexpected peak demand.

2 Data Center

Computing demand and cooling load can rise simultaneously, increasing power uncertainty.

Robust optimization improves reliable operation under sudden demand surges.

3 EV Charging Hub

Vehicle arrival time, charging duration, and charging power are difficult to predict.

Robust optimization prepares the EMS for high-demand charging scenarios.

03. Robust Optimization

■ Advantages of Applying Robust Optimization – Case Study: Railway Station

Railway Station

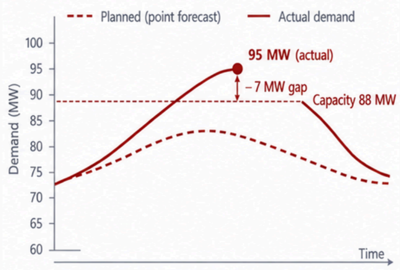
- Regenerative braking energy occurs during train stops and is managed by ESS.
- Passenger surges during commuting hours cause significant load fluctuations.
- HVAC demand varies with weather and occupancy.

Before — Point Forecast Only

Numerical Example (peak hour 18:00)

• Point forecast (planned):	80 MW
• Reserve secured (10%):	+8 MW
• Capacity available:	88 MW
• Actual demand (peak):	95 MW

→ Shortfall: 7 MW (unserved energy)



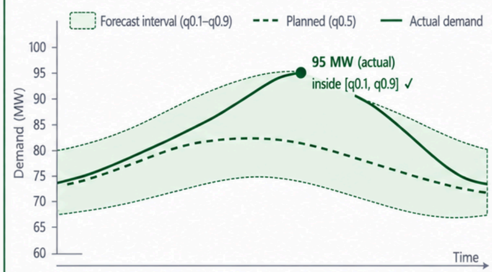
Reserve was insufficient → operation risk

After — Quantile Interval + Robust Optimization

Numerical Example (peak hour 18:00)

• Baseline forecast (q0.5):	80 MW
• Upper quantile (q0.9):	96 MW
• Reserve = q0.9 − q0.5:	+ 16 MW
• Actual demand (peak):	95 MW ✓ within interval

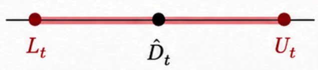
→ Shortfall: 0 MW (demand fully covered)



Reserve covers actual peak → stable EMS operation

■ Robust Optimization

1. Forecast Interval and Reserve Requirement



$$L_t = q_{low,t}, \quad \hat{D}_t = q_{0.5,t}, \quad U_t = q_{high,t}$$

$$D_t \in [L_t, U_t]$$

$$RU_t = \max(U_t - \hat{D}_t, 0)$$

$$RD_t = \max(\hat{D}_t - L_t, 0)$$

- Quantile forecasts represent demand uncertainty as an interval.
- The interval is converted into upward and downward reserve requirements.

2. Robust Optimization Formulation

Objective

$$\min \sum_t \left[C_{gen}(P_t) + C_{ESS}(ch_t, dis_t) + C_{pen} \cdot x_t\right]$$

Main constraints

$$P_t + dis_t - ch_t = \hat{D}_t$$

$$RU_t^{plan} \geq U_t - \hat{D}_t$$

$$RD_t^{plan} \geq \hat{D}_t - L_t$$

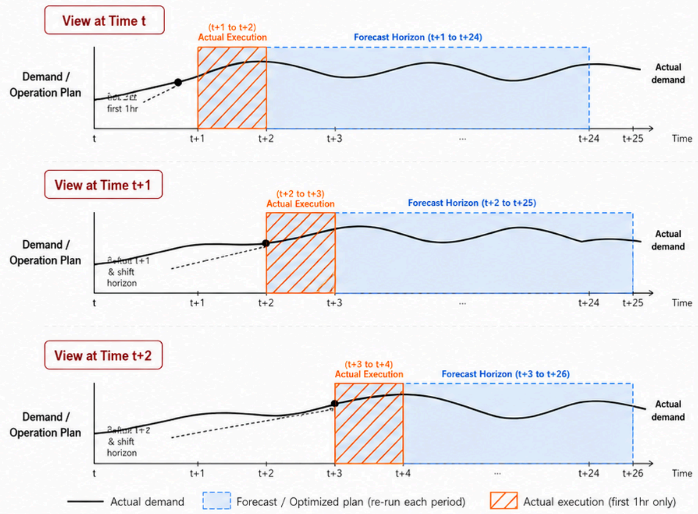
$$SOC_{t+1} = SOC_t + \eta_{ch} ch_t - dis_t / \eta_{dis}$$

$$P_t^{min} \leq P_t \leq P_t^{max}$$

$$SOC^{min} \leq SOC_t \leq SOC^{max}$$

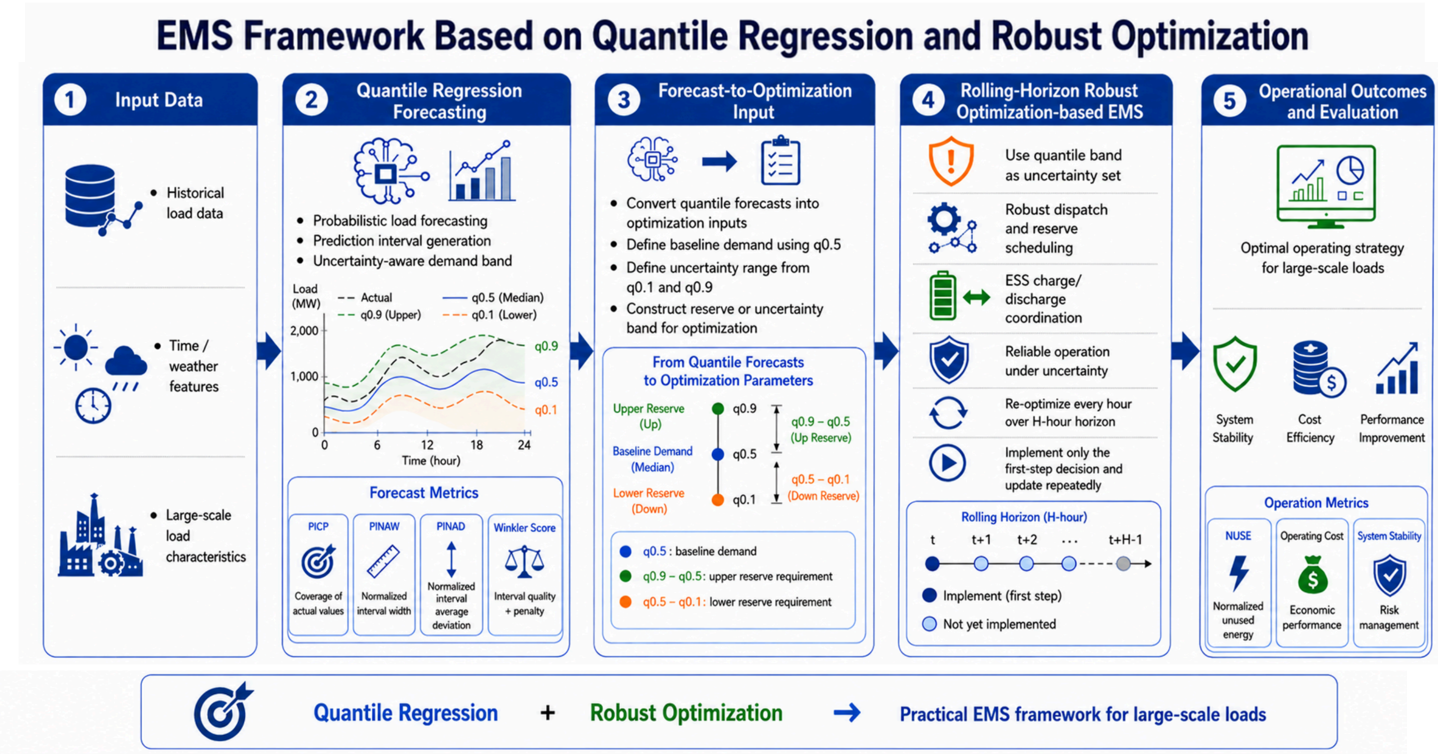
3. Rolling-Horizon Optimization

- Re-forecast and re-optimize every hour
- Execution of only the first-hour decision
- Shift the horizon forward and repeat



4. EMS Framework Implementation

04. EMS Framework Implementation



5. Simulation

05. Simulation

DATA

1. Data Source

- Korea Power Exchange (KPX) public data
- Nationwide hourly power demand data
- Data fields: date, time, power demand (MWh)
- 2020 and 2021 data were downloaded separately and then merged

2. Overview of the Dataset

Dataset	KPX nationwide power demand
Time period	Jan. 1, 2020 – Dec. 31, 2021
Training data	2020 (1 year)
Test / validation	2021 (1 year)
Resolution	1 hour
Total data points	17,543
Unit	MWh
Target variable	System load (Demand)
Forecasting features	lag1, lag24, lag168, hour, sin, hour_cos

3. Data Scaling

Purpose	Adapt nationwide demand data to a microgrid-scale EMS environment
Original peak demand	94,500 MW
Target peak demand	101 MW
Method	Temporal pattern preserved, only magnitude reduced
Main use	Quantile forecasting for interval-based robust EMS optimization

Scaled demand = Original demand × (101 MW / Original peak demand)

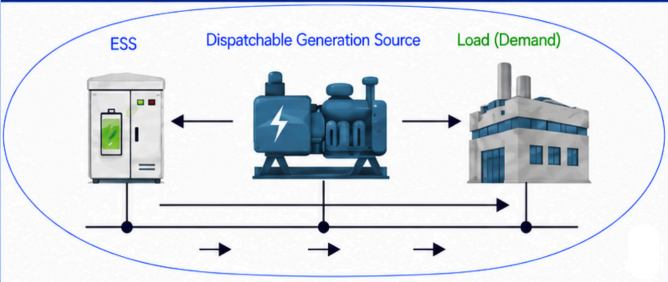
Scaled demand = Original demand × (101 MW / 94,500 MW)

4. Simulation Resource Parameters

Dispatchable Generation Source	
Maximum output	100 MW
Minimum output	10 MW
Ramp rate	10 MW/h
Generation cost	75,000 KRW/MWh

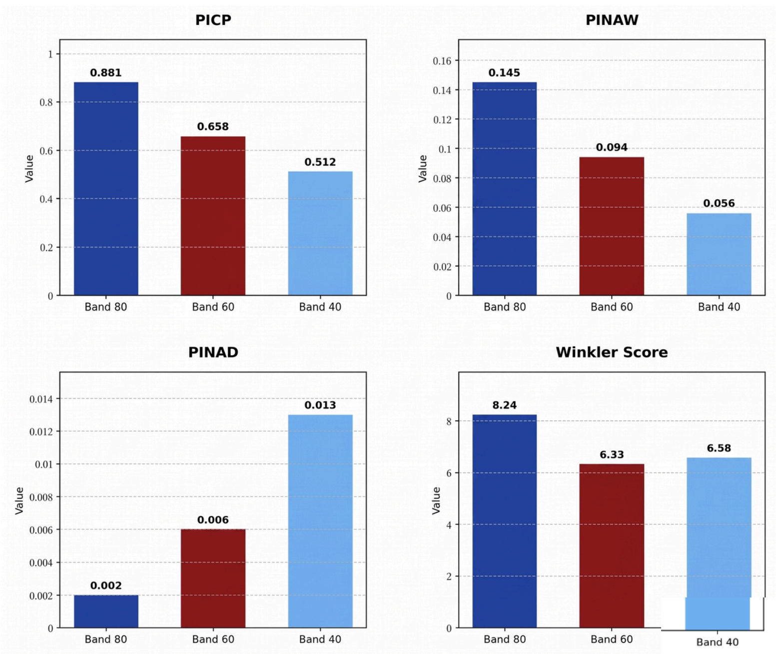
ESS	
Energy capacity	24 MWh
Max charge / discharge power	24 MW
Charge efficiency	0.97
Discharge efficiency	0.97
SOC range	10% ~ 90%
Initial SOC	50%

5. Microgrid Configuration



05. Simulation

Result 1 – Forecast Evaluation



- **PICP**

  In all quantile bands, the actual PICP exceeded the nominal coverage level
  → indicating that the prediction intervals secured demand coverage beyond the target level

- **PINAW / PINAD**

  PINAW (efficiency) and PINAD (reliability) exhibit an inverse relationship, preventing band selection based on a single metric

- **Winkler Score**

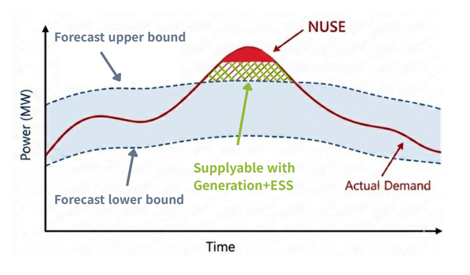
  Winkler Score applied as the final criterion by simultaneously reflecting interval width and deviation penalty

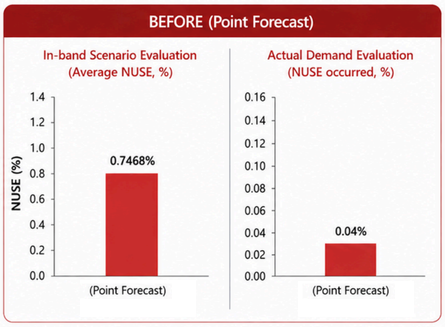
⟶ **Final conclusion**

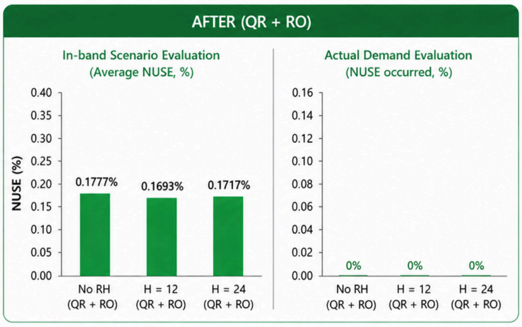
Band 60, yielding the lowest overall Winkler Score, identified as the optimal forecasting interval satisfying both economic efficiency and reliability

■ Result 2 – Variability Control

NUSE(%) (Normalized unserved energy)







- **Definition**

  Normalized index of annual unserved energy

- **Formula:**

$$\text{NUSE}(\%) = \frac{\text{Total unserved energy}}{\text{Total Demand}} \times 100\%$$

- **Point Forecast**

– Reliance on a single forecast value leading to insufficient reserve procurement

– Immediate outage (NUSE) occurrence under forecast errors

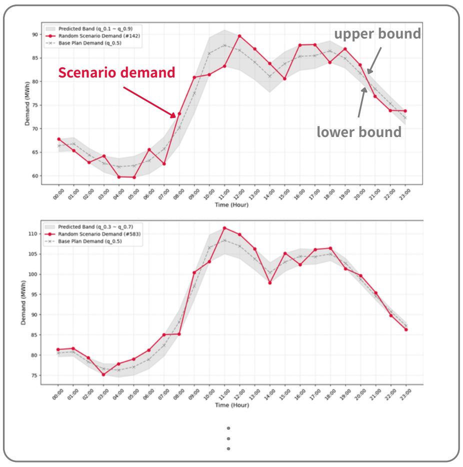
- **QR+Robust**

– Preparation for worst-case scenarios based on QR forecasting

– Stable supply-demand balance achieved even under actual demand fluctuations

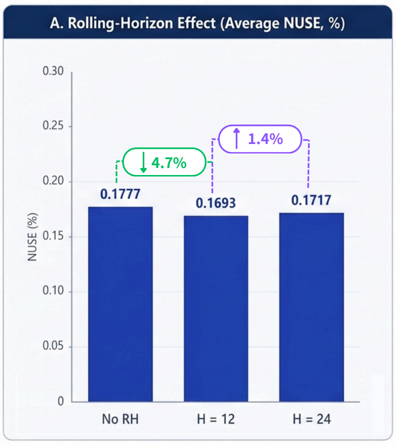
■ Result 3 – Evaluation of Robustness under Scenario-based Testing

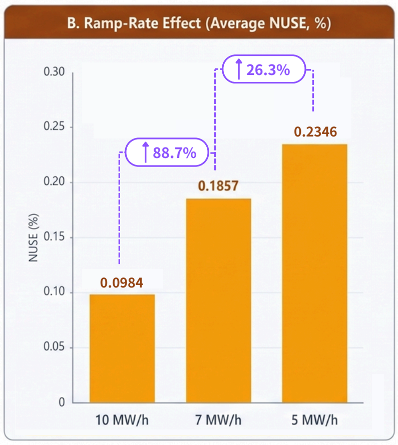
multiple scenario



Each scenario composed solely of the upper (q0.9) and lower (q0.1) bound values of the forecast interval

→ representation of the most extreme demand realizations within the predicted range.





- Minimum NUSE at H = 12.
- Increase in NUSE due to reduced generator flexibility under lower ramp rates.

- Increase in NUSE due to reduced generator flexibility under lower ramp rates.

⟶ **Ramp rate is the dominant factor affecting robustness.**

6. Conclusion

06. Conclusion

■ Summary

- Applied quantile regression and robust optimization to handle demand variability and forecast uncertainty in EMS scheduling. Reserve was secured within the forecast interval, and rolling horizon operation eliminated unserved energy under uncertain demand.

■ Suitable Applications

- Effective for large-scale loads with high demand variability (railway stations, data centers, and EV charging hubs.)

■ Limitations

- EMS framework: does not yet include unit commitment(UC) constraints or detailed generator characteristics.
- Simulation: generator and ESS models were simplified, so results may differ from real-system operation.

■ Future Work

- Incorporate UC constraints and realistic generator characteristics into the EMS framework.
- Extend the simulation with detailed component models and field-level data for higher fidelity.

Thank you