Multi-Objective Estimation of Prediction Intervals for Probabilistic Forecasting: Application to Solar Power Forecasting

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Outline

Introduction: Probabilistic forecast

Probabilistic forecast: Determine uncertainty information of y and provide statistical information of y

Uncertainty representation: **Prediction interval (PI)** shows possible outcomes with upper and lower bounds at a specified confidence level.

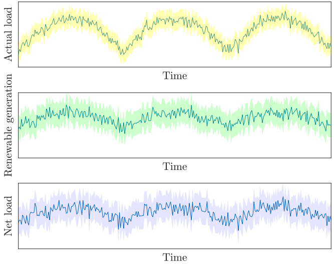
The quality of PI is assessed by reliability (PICP) and sharpness (PI width), which have trade-off behavior.

Application of probabilistic forecast

- Solar [MWM18; LZ20]
- Wind [ZWW14]
- Electrical load [HF16; Zha+20]
- Electricity price [KNC13; NW18]

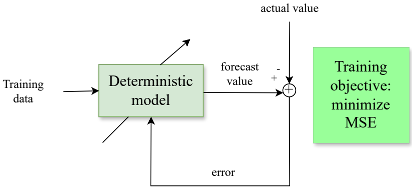
Example of decision making application

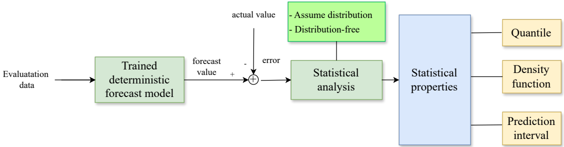
- Reserve power preparation [ZWS21]
- Unit commitment [Cor+18]
- Economic dispatch [AGM18]
- Robust energy management system [Don+24]



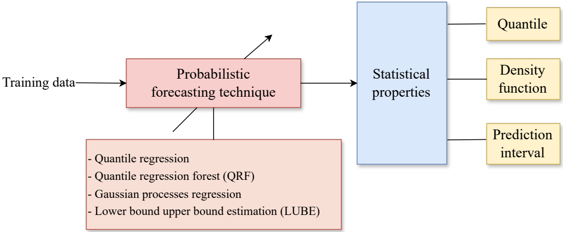
Introduction: The PI construction approach

Indirect approach

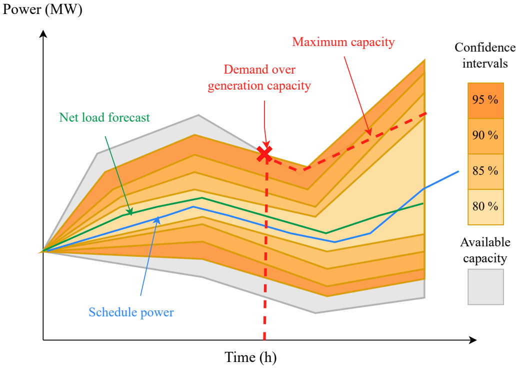




Direct approach



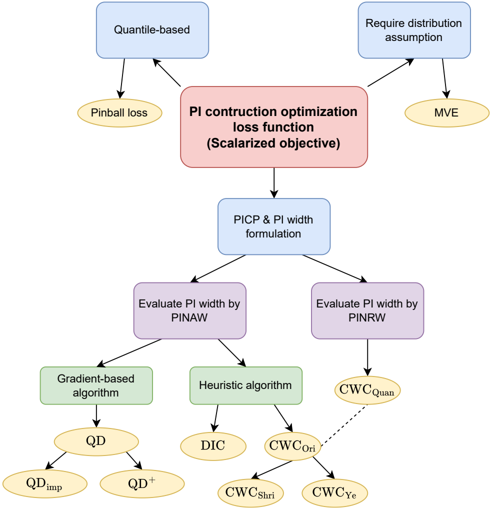
Motivation: Cost of large PI widths in power system application



Using PIs in power operation

- A wider PI requires a larger reserve margin, resulting in higher costs
- Some instances of larger PI widths can result in increased reserve power preparation throughout the day in unit commitment or economic dispatch
- The scheme emphasizes the worst-case scenario, particularly with large PI width. Reducing this width can lessen the conservatism of the optimized solution
- The reduction in large PI width leads to lower operating costs while maintaining reliability, preventing over-allocation of reserve resources

Previous works on formulating PI construction as optimization problem



- Scalarized objectives usually have two terms: PICP and PI width control, which can be in multiplication or additive form
- The PI width component is commonly evaluated using metrics such as PINAW or PINRW
- This thesis mainly proposes a new PI width function that reduces the large PI width

Thesis overview

Objectives:

1. provides a probabilistic forecast of solar power in the form of PI, assisting users in decision-making for energy management.
2. proposes optimization formulations to construct a PI that encourages a trade-off characteristic between two objectives: high coverage and narrower PI width.

Scope of work:

1. Probabilistic forecasts are provided in terms of PI
2. The concept is illustrated in solar data collected in Thailand

Expected outcome:

1. A methodology that generates quality-based PI for probabilistic forecasts, emphasizing high reliability and sharpness.
2. A software package that returns the PIs corresponding to a given confidence level

Background: QR, QRF, PI estimation

Setting: given a dataset $\{(x_i, y_i)\}_{i=1}^{N}$ where x_i, y_i represent a predictor and a target variable, and θ is model parameters

Quantile regression (QR) - Indirect PI

QR estimates the α^{th} conditional quantile of the target variable by minimizing the pinball loss as

$$\underset{\theta}{\text{minimize}} \quad \sum_{i=1}^{N} \rho_\alpha(y_i - \hat{y}_i(x_i;\theta))$$

where $\rho_\alpha(r) = \max(\alpha r, (\alpha - 1)r)$

Quantile regression forest (QRF) - Indirect PI

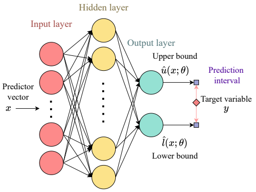
QRF is a tree-based method that provides the full conditional CDF $\hat{F}(y|x)$ of the target variable

Two quantiles can be defined as the lower and upper bounds

PI estimation - Direct PI

PI estimation is a statistical tool that quantifies the overall uncertainty of y by providing the interval $\left(\hat{l}, \hat{u}\right)$ directly with a confidence level of $(1-\delta) \times 100\%$ as

$$\textbf{prob}(\hat{l}(x;\theta) \leq y \leq \hat{u}(x;\theta)) = 1 - \delta$$



In the direct PI approach, models with parameters θ learn to directly map the input to the PI

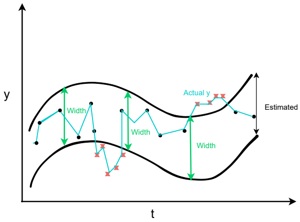
Background: Evaluation metrics for PI

Reliability $\rightarrow$ PICP, Sharpness $\rightarrow$ width

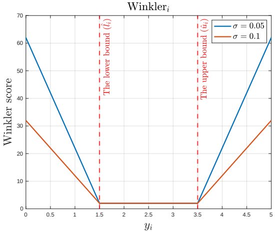
- **Prediction interval coverage probability (PICP):**
  $\mathrm{PICP} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}(\hat{l}_i \leq y_i \leq \hat{u}_i)$
- **Prediction interval average width (PINAW):**
  $\mathrm{PINAW} = \frac{1}{NR}\sum_{i=1}^{N} (\hat{u}_i - \hat{l}_i)$ where $R = y_{\max} - y_{\min}$
- **Winkler score:** with confidence level $(1-\delta) \times 100\%$

$$\mathrm{Winkler}_i = \begin{cases} |\hat{u}_i - \hat{l}_i| + \frac{2}{\delta}(\hat{l}_i - y_i), & y_i < \hat{l}_i \\ |\hat{u}_i - \hat{l}_i|, & \hat{l}_i \leq y_i \leq \hat{u}_i \\ |\hat{u}_i - \hat{l}_i| + \frac{2}{\delta}(y_i - \hat{u}_i), & y_i > \hat{u}_i \end{cases}$$

$$\mathrm{Winkler} = \frac{1}{NR}\sum_{i=1}^{N} \mathrm{Winkler}_i$$

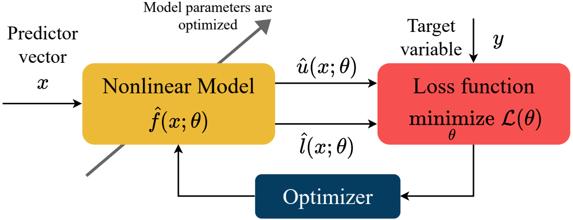


Prediction interval



Winkler score

Methodology: Training mechanism



The methodology for the training mechanism of the PI construction.

- Nonlinear model: NN model with two outputs
- Loss function: Define the objective of learning
- Optimizer: Numerical method used to minimize the proposed loss (Adam)

Methodology: Mathematical formulation

Given the sample width of PI is $w_i = \hat{u}_i - \hat{l}_i$, the i^{th} largest PI width is $w_{[i]}$, with $w_{[1]} \geq w_{[2]} \geq \ldots \geq w_{[N]}$

The proposed Sum-k loss: stronger penalize on the large PI widths

$$\mathcal{L}_{\text{Sum}-k}(\theta|\gamma, K, \lambda) = \max(0, (1-\delta) - \text{PICP}(\theta)) + \gamma \frac{1}{R_Q}\left[\frac{1}{K}\sum_{i=1}^{K} w_{[i]}(\theta) + \frac{\lambda}{N-K}\sum_{K+1}^{N} w_{[i]}(\theta)\right]$$

Coverage term

Given a smooth approximation of the count function:

$$\mathbf{1}_{\tanh}(\hat{l} \leq y \leq \hat{u}) = \frac{1}{2}\max\left[0, \tanh(s(y-\hat{l})) + \tanh(s(\hat{u}-y))\right]$$

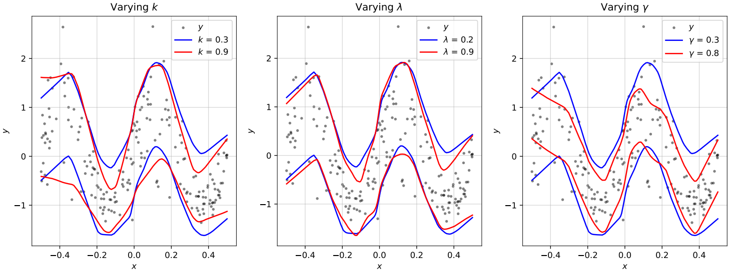
The smooth version of PICP is calculated as

$$\text{PICP}(\theta) = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}_{\tanh}(\hat{l}_i \leq y_i \leq \hat{u}_i), \quad s = 50$$

PI width control term

- γ controls the trade-off between coverage and PI width
- K is the fraction of data categorized as large PI widths set as $\lfloor kN \rfloor$where $k \in (0,1)$
- $\lambda > 0$ is a relative weight of the averaged narrow PI widths
- $R_Q = q_y(0.95) - q_y(0.05)$ is the normalization factor to scale the PI width term and eliminate the effect of outliers

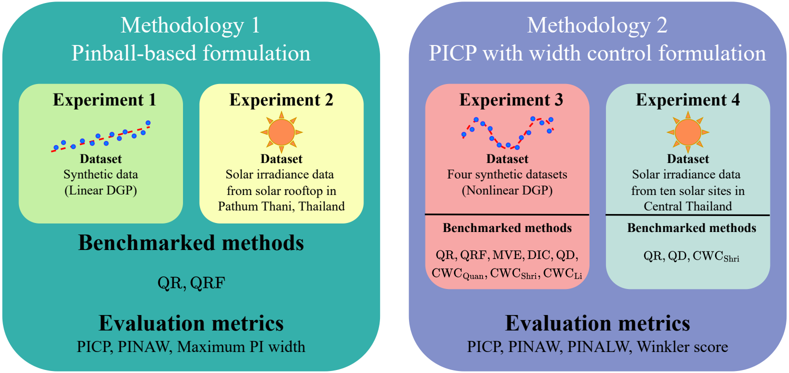
Methodology: Effect of each hyperparameters



The effect of formulation hyperparameters.

- k: setting lower k highlights the different penalization between large and narrow PI widths.
- λ: decreasing λ places relatively greater emphasis on large PI widths.
- γ: increasing γ reduces the PI width while decreasing PICP. Suggest a tuning on the validation set

Overview of the experiments



The overall of the experiment.

- **Methodology 1** includes formulation P1, P2, and P3
- **Methodology 2** includes Sum-k loss
- **Metric to measure the large PI width**
  PINALW $= \frac{1}{KR_Q}\sum_{i=1}^{K} w_{[i]}$,
  where $K = \lfloor (1-p)N \rfloor$

Benchmarked loss

All methods are formulated as the loss to be minimized, equipped with the NN model, except QRF.

Quantile-based methods

QR $=$
$$\frac{1}{N}\left[\sum_{i=1}^{N} \rho_{\delta/2}(y_i - \hat{l}(x_i;\theta)) + \rho_{1-\delta/2}(y_i - \hat{u}(x_i;\theta))\right]$$

QRF (tree-based)

Assume Gaussian distribution

$$\text{MVE} = \frac{1}{2}\sum_{i=1}^{N}\left(\log(\hat{\sigma}^2(x_i;\theta)) + \frac{(y_i-\hat{\mu}(x_i;\theta)))^2}{\hat{\sigma}^2(x_i;\theta)}\right)$$

PI width-based loss function

$$\text{CWC}_{\text{Quan}} = \text{PINRW}(1 + e^{\gamma\max(0,(1-\delta)-\text{PICP})})$$

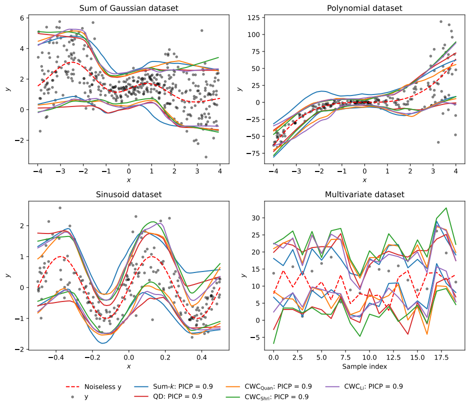
$$\text{CWC}_{\text{Shri}} = \text{PINAW} + e^{\gamma\max(0,(1-\delta)-\text{PICP})}$$

$$\text{CWC}_{\text{Li}} = \frac{\beta}{2}\text{PINAW} + \left(\alpha + \frac{\beta}{2}\right)e^{\gamma\max(0,(1-\delta)-\text{PICP})}$$

$$\text{DIC} = \text{PINAW} + \mathbf{1}(\text{PICP} < 1-\delta)\cdot \mathrm{pun}$$
$$\text{where } \mathrm{pun} = \gamma\left[\sum_{i=1}^{N_L}(\hat{l}_i - y_i) + \sum_{i=1}^{N_U}(y_i - \hat{u}_i)\right]$$

$$\text{QD} = \max(0, (1-\delta) - \text{PICP})^2 + \gamma\text{PINAW}_{\text{capt.}}$$

Experiment 3: Experiment setting



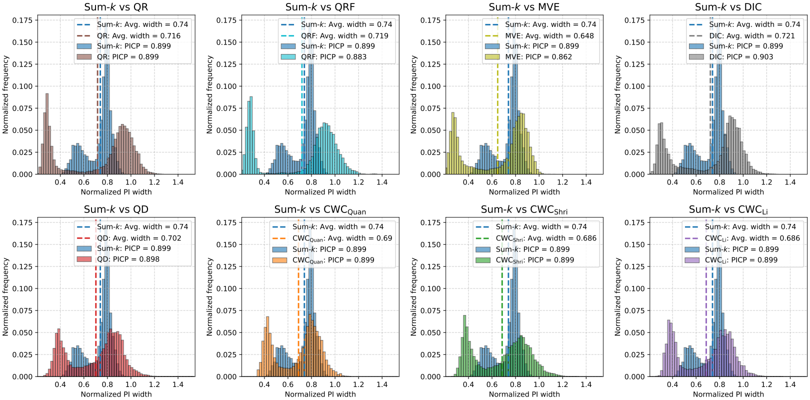
The synthetic datasets and the PI characteristics.

- **Dataset** Four datasets with each 100 trials of noise
- **Model architechture** ANN

Model specification	Setting
Hidden layers	3
Neurons per layer	no. of input features, 100, 100, 100, 2
Activation function	ReLU
Batch Normalization	Added after hidden layers
Total number of trainable parameters	21,102 + no. of input features $\times$ 100

- **Setting**
  Confidence level: $(1 - \delta) = 0.9$
  Sum-k: set $k = 0.3, \lambda = 0.1$
  Operating point: Vary γ and select the operating point with 0.9 PICP
  Algorithm parameter: `lr` depends on the loss, $\texttt{max\_epochs} = 2000, \texttt{patience} = 100$

Experiment 3: Results



Comparison of the PI width histogram aggregated across 100 trials in the sum of the Gaussian dataset.

Sum-k benefits

- Maintain 0.9 PICP
- Least variation of PI widths
- Effectively reduces the large PI widths

Drawbacks from benchmarked methods (found in the multivariate dataset)

- Slow convergence in CWC_{Quan}, CWC_{Li}, DIC
- MVE fails to reach 0.9 PICP

Experiment 4: Solar forecasting application

Objective: Demonstrate the effectiveness of the proposed method for reducing the large PI widths in solar irradiance forecasting, which involves a high level of uncertainty due to fluctuating weather conditions

Forecasting Specification: Generate one-hour-ahead PIs for solar irradiance from 07:00 to 17:00, with a 15-minute resolution and a 0.9 confidence level

Dataset:

The target variable is $I(t+15), I(t+30), I(t+45), I(t+60)$.

Lagged regressor: four lags: $t-45, t-30, t-15, t$

Measurement data (I): collected from ten solar sites in Central Thailand during January - December 2023, provided by DeDe.

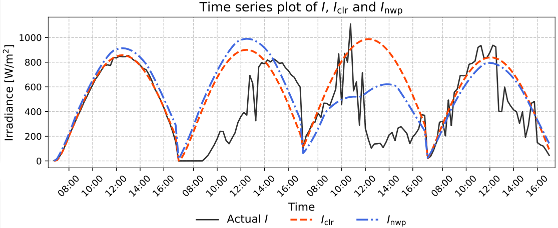
Cloud index (CI_R): extracted from R-channel of cloud images sourced from the Himawari-8 satellite with a spatial resolution of $2 \times 2\mathrm{km}^2$. Then, the cloud index is calculated as $\mathrm{CI} = \frac{X-\mathrm{LB}}{\mathrm{UB}-\mathrm{LB}}$.

Future regressor: four steps: $t+15, t+30, t+45, t+60$

Clear-sky irradiance (I_{clr}): obtained from Ineichen clear-sky model

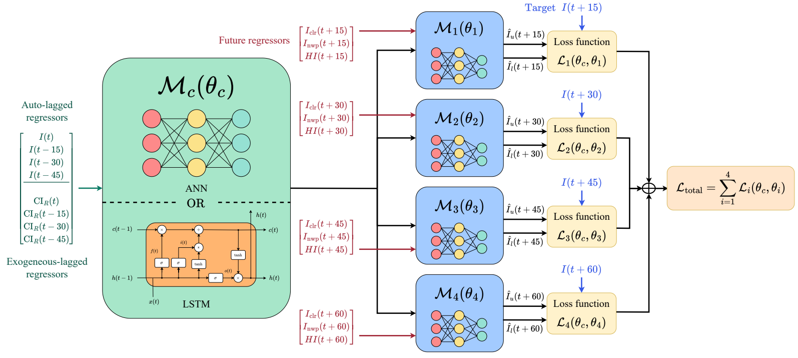
Forecasted NWP irradiance (I_{nwp}): obtained from the reanalyzed MERRA-2

Hour index (HI): represent hour of the day



Total: 113,793 samples

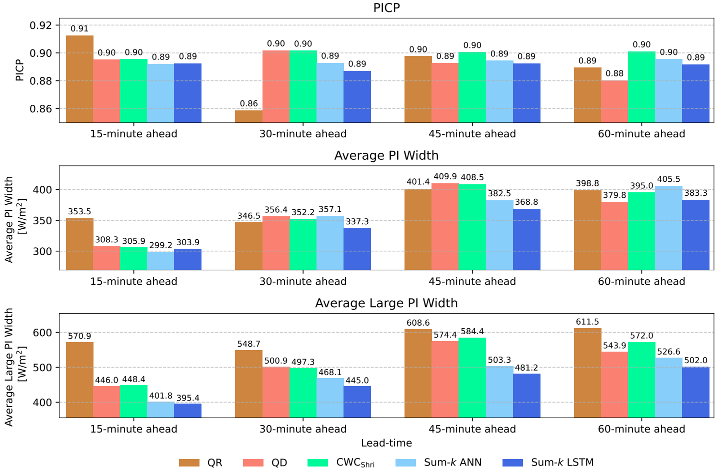
Experiment 4: Model architechture



The NN model architecture used in the solar data experiment includes a common. model $\mathcal{M}_C$ and a submodel $\mathcal{M}_i$, where the PI outputs with the target are used to evaluate the loss function.

- $\mathcal{M}_C$ handles lagged regressors, and shares input layer across all lead times
- $\mathcal{M}_i$ handles the input aligning with the specific lead time
- Total model parameters: 95,808 for ANN, and 99,278 for LSTM

Experimet 4: Results



PI evaluation on the test set in the unit of W/m^2.

- The method that has γ can achieve PICP at 0.9 across all lead times
- QR does not guarantee achieving the desired PICP
- The proposed loss has the lowest PINALW across all lead times

Experiment 4: Results

Comparison of evaluation metrics on the test set of one-hour-ahead solar irradiance forecasting with a controlled PICP at 0.9.

15-minute ahead				
Method	**PINAW**	**Winkler**	**PINALW**	**Reduction ratio**
QR	0.395	**0.484**	0.638	30.7%
QD	0.345	0.572	0.499	11.3%
CWC_{Shri}	0.342	0.611	0.501	11.8%
Sum-k ANN	**0.335**	0.656	0.449	1.6%
Sum-k LSTM	0.340	0.675	**0.442**	-

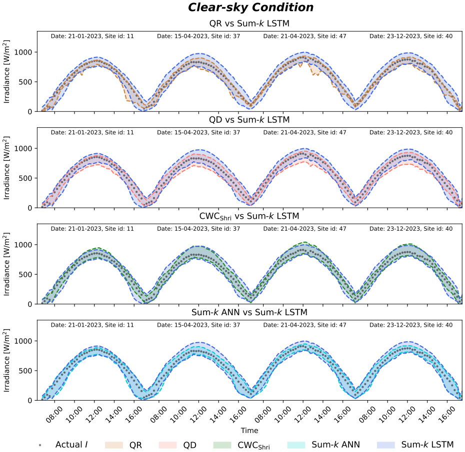
30-minute ahead				
Method	**PINAW**	**Winkler**	**PINALW**	**Reduction ratio**
QR	0.388	**0.547**	0.614	18.9%
QD	0.399	0.627	0.560	11.2%
CWC_{Shri}	0.394	0.647	0.556	10.5%
Sum-k ANN	0.399	0.694	0.523	4.9%
Sum-k LSTM	**0.377**	0.666	**0.498**	-

45-minute ahead				
Method	**PINAW**	**Winkler**	**PINALW**	**Reduction ratio**
QR	0.449	**0.569**	0.681	20.9%
QD	0.458	0.644	0.642	16.2%
CWC_{Shri}	0.457	0.643	0.653	17.7%
Sum-k ANN	0.428	0.716	0.563	4.4%
Sum-k LSTM	**0.412**	0.694	**0.538**	-

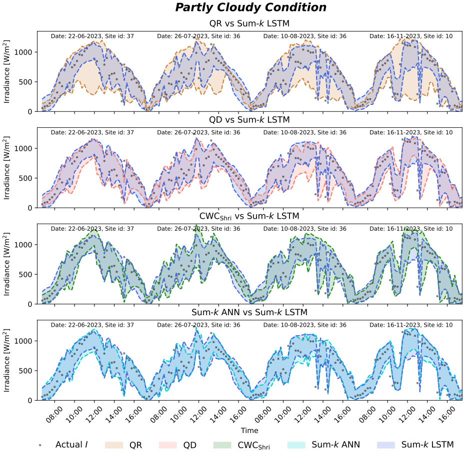
60-minute ahead				
Method	**PINAW**	**Winkler**	**PINALW**	**Reduction ratio**
QR	0.446	**0.579**	0.684	17.9%
QD	**0.425**	0.676	0.608	7.7%
CWC_{Shri}	0.442	0.684	0.640	12.2%
Sum-k ANN	0.454	0.704	0.589	4.7%
Sum-k LSTM	0.429	0.713	**0.561**	-

- QR achieves the best Winkler score
- The Sum-k with LSTM can reduce the large PI width in a ratio varying from 7.7% to 30.7%
- The reduction PI width in I can be convert to P

Experiment 4: Results

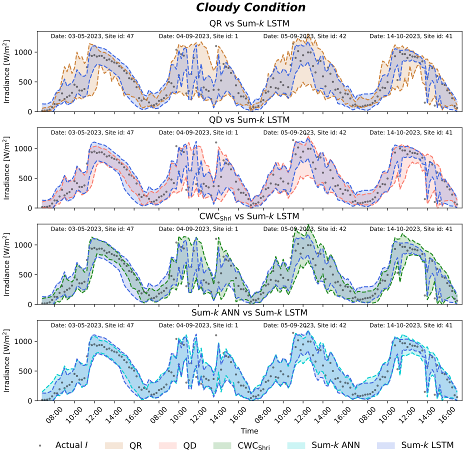


PI of 15-minute ahead PI solar forecast in clear-sky condition.



PI of 15-minute ahead PI solar forecast in partly cloudy condition.

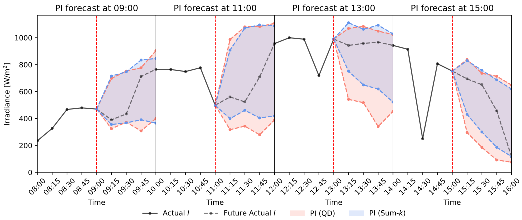
Experiment 4: Results



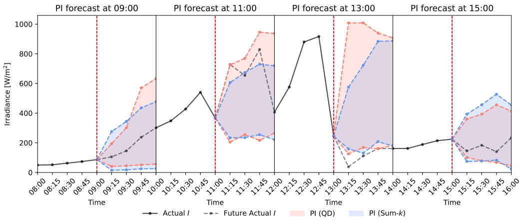
PI of 15-minute ahead PI solar forecast in cloudy condition.

- The Sum-k can effectively reduce the PI width in high uncertainty data found in partly cloudy and cloudy conditions
- With an appropriate λ, the PI width from Sum-k performs comparably to benchmark methods
- The Sum-k with LSTM has lower validation loss than ANN
- For Sum-k, LSTM reduces the large PI widths more effectively

Experiment 4: Results on real operation



Actual future irradiance is covered by PIs.

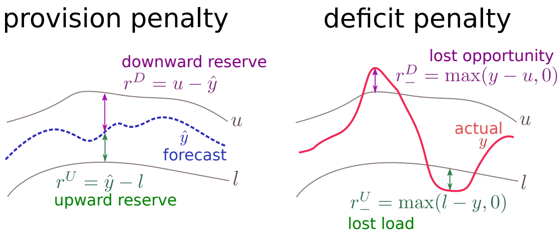


Actual future irradiance is not covered by PIs.

- At time t, the 4-step ahead PIs are released
- Sum-k exhibits a narrower PI width compared to QD in a high uncertainty situation
- With a confidence level of 0.9, there is a possibility that the actual I may fall outside the PI

Effectiveness of the proposed methods on engineering system applications

Cost evaluation in reserve preparation



Four types of reserves quantification using PIs.

Reserve price penalty	Price ($/MWh)
π^U	5.5, 8.25
π^D	0.08, 0.12
π^U_-	50, 500
π^D_-	30

The reserve price.

Objective: A solar power provider uses the point forecast $\hat{y}$ and PI $[\hat{l}, \hat{u}]$ information to plan the reserve amount necessary to maintain power balance under uncertainty

Planning operation

Upward reserve: Additional generation capacity that must be scheduled in advance

Downward reserve: Mitigation strategies that must be planned to reduce generation if necessary

Real-time operation

Lost load: Failure to deliver the committed generation, resulting in unserved demand

Lost opportunity: Excess generation that must be curtailed due to operational constraints

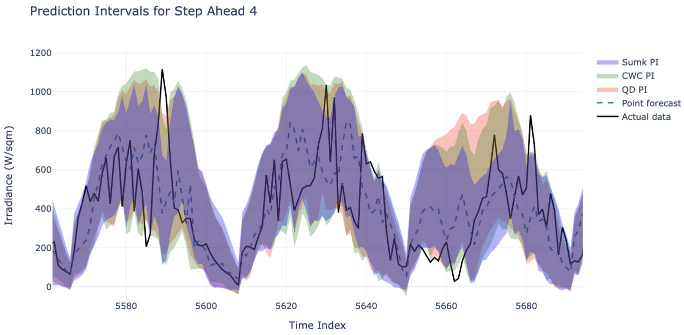
Total operating reserve cost ($)

$$\sum_{\forall t} \left(\pi^U r^U(t) + \pi^D r^D(t) + \pi^U_- r^U_-(t) + \pi^D_- r^D_-(t)\right) \Delta t$$

Setting:

Point forecast: Trained with *pinball loss* at 0.5 quantile using the PI model architecture

PI: Resulted from solar experiment (*Excluding QR due to crossing PI*)



Point forecast with PI in 4-step ahead forecast.

Cost evaluation dataset:

Test set with 15-minute resolution,
spanning 4 months,
evaluate each step-ahead cost separately

Power conversion:

Convert irradiance (W/m^2) to solar power assuming 100 MW installed capacity.

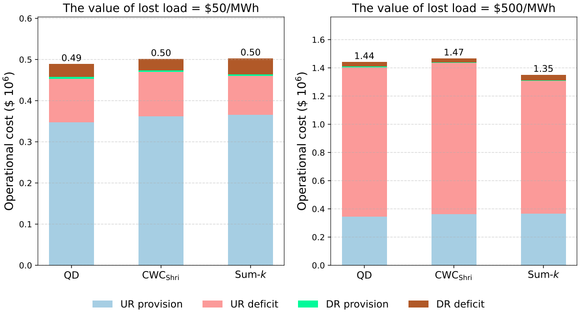
Cost evaluation in reserve preparation: Results

Reserve quantities in MWh calculated as $r = \sum_{\forall t} r(t)\Delta t$.

	1-step ahead			4-step ahead		
	QD	CWC_{Shri}	Sum-k	QD	CWC_{Shri}	Sum-k
r^U	50,485.2	46,504.2	44,832.9	57,273.3	59,208.5	63,331.0
r^U_-	1,302.0	1,863.2	2,262.9	2,117.6	2,146.5	1,886.1
r^D	36,475.3	39,787.2	39,560.5	49,851.3	52,196.2	51,057.5
r^D_-	1,564.8	1,524.9	1,793.6	1,050.6	906.1	1,277.5

- The Sum-k in the first step has the lowest PI width, leading to the lowest $r^U + r^D$
- Effective PI construction methods should achieve good r^U, r^D (from narrow PI width), reflecting the amount of reserve required before real-time operation

Cost evaluation in reserve preparation: Results

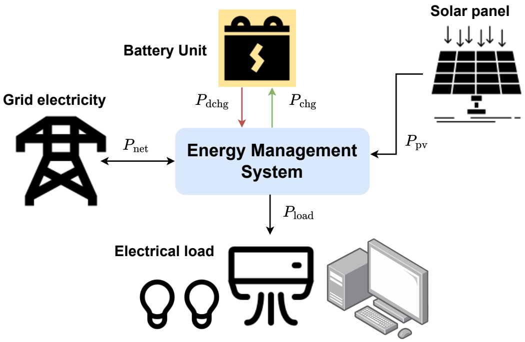


The solar power reserve cost estimated using 60-minute ahead forecasts.

- When VoLL $= \$50/\mathrm{MWh}$, the reserve price is comparable to the PINAW result, the upward reserve cost is dominant
- When VoLL $= \$500/\mathrm{MWh}$, the Sum-$k$ has the lowest total cost because the lower bound effectively captures actual generation
- In practice, the VoLL could reach up to $\$9{,}000/\mathrm{MWh}$; thus, the Sum-$k$ would significantly save costs compared to others

Impact of PI width in robust energy management: EMS components

EMS can be implemented in a small building equipped with PV and a battery storage system to control battery charging and discharging, thereby optimizing energy usage and reducing net electricity costs.



The element of a small building energy management system (BEMS).

- Electrical load: consumes power (requires forecasting)
- Solar panel: generates power (requires forecasting)
- Battery unit: stores energy from the grid or PV (controlled by EMS)
- External grid: connected to EMS for energy import/export

Net load: $P_{\text{net load}} = P_{\text{load}}(t) - P_{\text{pv}}(t)$

Power balance: $P_{\text{net}}(t) = P_{\text{net load}}(t) + P_{\text{chg}}(t) - P_{\text{dchg}}(t)$

$P_{\text{net}}(t) > 0$ power is drawn from the grid

$P_{\text{net}}(t) < 0$ excess PV power is fed back to the grid

Impact of PI width in robust energy management: EMS optimization formulation

EMS optimization formulation can be written as:

The optimization formulation of EMS

$$
\begin{aligned}
\text{minimize} \quad & J_{\text{cost}} + w_b J_{\text{batt}} \\
\text{subject to} \quad & P_{\text{net}}(t) = P_{\text{net load}}(t) + P_{\text{chg}}(t) - P_{\text{dchg}}(t) \\
& \text{SoC}(t+1) = \text{SoC}(t) + \frac{100\%}{\text{BattCapacity}} \left(\eta_c P_{\text{chg}}(t) - \frac{P_{\text{dchg}}(t)}{\eta_d} \right) \Delta t \\
& 0 \leq P_{\text{chg}}(t) \leq \text{max charge rate}, \quad 0 \leq P_{\text{dchg}}(t) \leq \text{max discharge rate} \\
& \text{SoC}_{\text{min}} \leq \text{SoC}(t) \leq \text{SoC}_{\text{max}}, \quad t = 1, 2, \ldots, T
\end{aligned}
$$

Objective functions

$$
J_{\text{cost}} = \Delta t \sum_{t=1}^{T} b(t) \max(0, P_{\text{net}}(t)) - s(t) \max(0, -P_{\text{net}}(t))
$$

$$
J_{\text{batt}} = \Delta t \sum_{i=1}^{T-1} |P_{\text{chg}}(t+1) - P_{\text{chg}}(t)| + \Delta t \sum_{i=1}^{T-1} |P_{\text{dchg}}(t+1) - P_{\text{dchg}}(t)|
$$

Problem parameter: $P_{\text{pv}}(t), P_{\text{load}}(t), P_{\text{net load}}(t) = P_{\text{load}}(t) - P_{\text{pv}}(t)$

Optimization variables: $P_{\text{chg}}(t), P_{\text{dchg}}(t)$

EMS: Integrate the uncertainty to EMS

Setting: $P_{\text{pv}}, P_{\text{load}}$ involve uncertainty due to their nature. We can utilize the PI construction method for $P_{\text{net load}}$ to capture the uncertainty represented in $[L, U]$ with a confidence level of $1 - \delta$.

The uncertainty set of the net load can be defined as

$$\mathcal{U} = \{P_{\text{net load}}(t) | L(t) \leq P_{\text{net load}}(t) \leq U(t)\}$$

$P_{\text{net}}(t) = P_{\text{net load}}(t) + P_{\text{chg}}(t) - P_{\text{dchg}}(t)$ becomes:

$$L(t) + P_{\text{chg}}(t) - P_{\text{dchg}}(t) \leq P_{\text{net}}(t) \leq U(t) + P_{\text{chg}}(t) - P_{\text{dchg}}(t)$$

$U(t)$ - Pessimistic: Robust EMS with uncertainty set

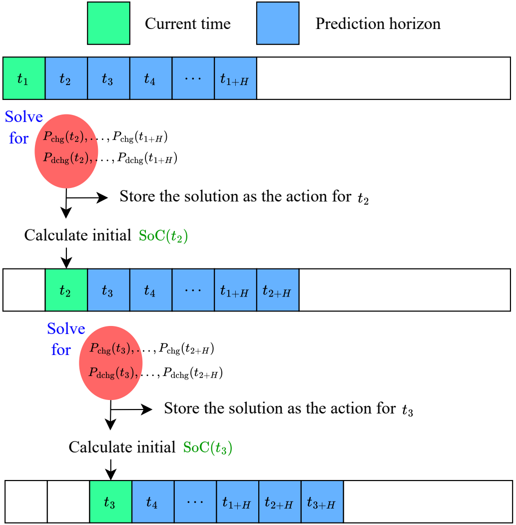
The robust EMS that minimizes the worst-case cost (occurs when the net load achieves its upper bound) can be formulated as

$$\begin{aligned} \text{minimize} \quad & J_{\text{cost}} + w_b J_{\text{batt}} \\ \text{subject to} \quad & P_{\text{net}}(t) = U(t) + P_{\text{chg}}(t) - P_{\text{dchg}}(t), \\ & \text{Battery constraints.} \end{aligned}$$

$L(t)$ - Optimistic: Robust EMS with chance constraint

The interval of $P_{\text{net}}(t)$ is equivalent to chance constraint $\textbf{prob}(P_{\text{net load}}(t) \in [L(t), U(t)]) = 1 - \delta$. Minimizing costs under the chance constraint results in $P_{\text{net}}(t)$ reaching its lower bound, as costs increase monotonically with $P_{\text{net}}(t)$. So, it can be formulated as

$$\begin{aligned} \text{minimize} \quad & J_{\text{cost}} + w_b J_{\text{batt}} \\ \text{subject to} \quad & P_{\text{net}}(t) = L(t) + P_{\text{chg}}(t) - P_{\text{dchg}}(t), \\ & \text{Battery constraints.} \end{aligned}$$



Rolling EMS optimization.

- At time t_1, the PI forecast of net load with H-steps ahead serves as problem parameters
- Solve the optimization variable at time t_1 to obtain $P_{\text{chg}}(t_1+1), \ldots, P_{\text{chg}}(t_1+H)$, and $P_{\text{dchg}}(t_1+1), \ldots, P_{\text{dchg}}(t_1+H)$ which provides a cost optimal battery profiles
- Apply the first time step $P_{\text{chg}}(t_1+1)$, $P_{\text{dchg}}(t_1+1)$ as the action for t_2
- Roll every 1 step, move from t_1 to t_2

EMS: Experiment setting

Objective: We aim to show the effectiveness of Sum-k in reducing large PI widths compared with QR, QD, and $\mathrm{CWC}_{\mathrm{Shri}}$, leading to lower uncertainty in estimating costs in robust EMS. Then, compare with the ideal case.

Specification: Require a four-hour horizon of (16 steps) net load forecast PI with a resolution of 15 minutes

Building system specification.

Specification	Value
Peak load	10 kW
PV capacity	5 kW
Battery capacity	25 kWh

Setting: Confidence level $= 0.9$, LSTM model, Sum-k - $k = 0.3, \lambda = 0.5$

EMS problem parameters and electricity tariffs.

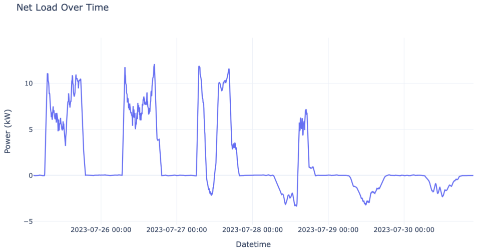
Parameter	Value	Parameter	Value (THB)
Battery		**Tariff**	
Charging efficiency	0.95	Buy rate (22:00-10:00)	2.7
Discharging efficiency	0.88	Buy rate (10:00-14:00)	5.7
Max charge rate	5 kW	Buy rate (14:00-18:00)	7
Max discharge rate	5 kW	Buy rate (18:00-22:00)	8
Minimum SoC	20 %	Sell rate (23:00-18:00)	2.2
Maximum SoC	80 %	Sell rate (18:00-23:00)	2.5

Dataset: spanned March - December

Lagged regressors (8 lags): $P_{\text{load}}, P_{\text{PV}}, P_{\text{net load}}, \mathrm{CI}_R$ from $t-15, \ldots, t-120$

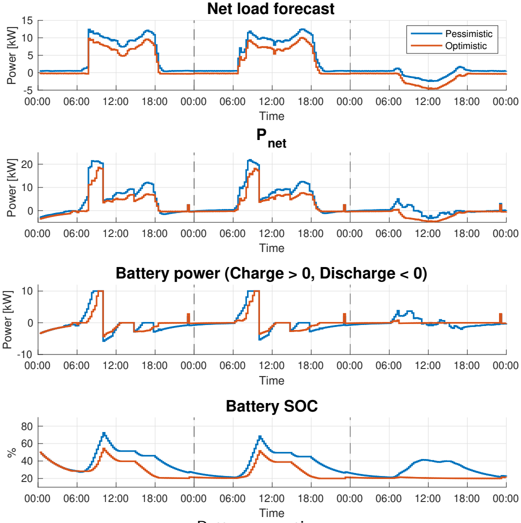
Future regressors (16 steps): $I_{\text{clr}}, I_{\text{nwp}}, T_{\text{nwp}}, \text{HI}, \text{Holiday}$

Target variable (16 steps): $P_{\text{net load}}$ from $t+15, \ldots, t+240$



Net load characteristics.

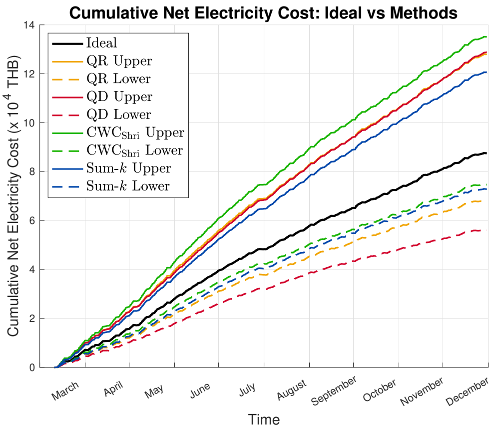
EMS: Results



Battery operation.

- Positive net load, the battery typically charges in the early morning
- The charging energy in the optimistic scenario is less than in the pessimistic scenario
- Negative net load, the optimistic sells all excess energy to the grid

EMS: Results



The cumulative cost over 10 months.

- The Sum-k demonstrates the smallest deviation, showing better PI quality in the robust EMS
- For the cumulative net electricity cost, the Sum-k has the lowest worst-case cost (upper bound) while also having the narrowest range of upper and lower bounds

Deviation of the net electricity cost from the ideal case.

Deviation from ideal	Pessimistic (%)	Optimistic (%)
QR	46.2	-22.2
QD	47.2	-36.0
CWC_{Shri}	54.4	-14.6
Sum-k	37.9	-16.8

Conclusion and limitation

Conclusion

- We proposed the Sum-k loss function to specially reduce the large PI width
- The Sum-k loss is compatible with gradient-based methods, allowing for the application of state-of-the-art NN
- The reduction in the large PI widths significantly reduces the operational cost in decision making
- The effectiveness of our method in reducing costs through the use of Sum-k is demonstrated in reserve preparation and robust EMS

Limitation

- The PI width from the Sum-k for low-volatile data could be broader than other methods
- Tuning γ requires multiple NN training
- A multi-task learning algorithm can be applied to automatically adjust γ

Publications

1. W. Amnuaypongsa, W. Wangdee and J. Songsiri, "Probabilistic Solar Power Forecasting Using Multi-Objective Quantile Regression," *2024 18th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2024, pp. 26-31, doi: `10.1109/PMAPS61648.2024.10667174`.
2. W. Amnuaypongsa, Yotsapat Suparanonrat, Natanon Tongamrak, and J. Songsiri, "Estimation of Solar Panel Efficiency in the Presence of Curtailment," *The 22nd International Conference on Electrical Engineering/Electronics, Computer, Telecommunication, and Information Technology (ECTI-CON 2025)* (Accepted)
3. W. Amnuaypongsa, W. Wangdee and J. Songsiri, "Neural Network-Based Prediction Interval Estimation with Large Width Penalization for Renewable Energy Forecasting and System Applications," `arXiv:2411.19181 [cs.LG]` (Submitted to Energy conversion and management: X, under review).

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