Skill-driven Model Training for Solar Forecasting with Sky Images

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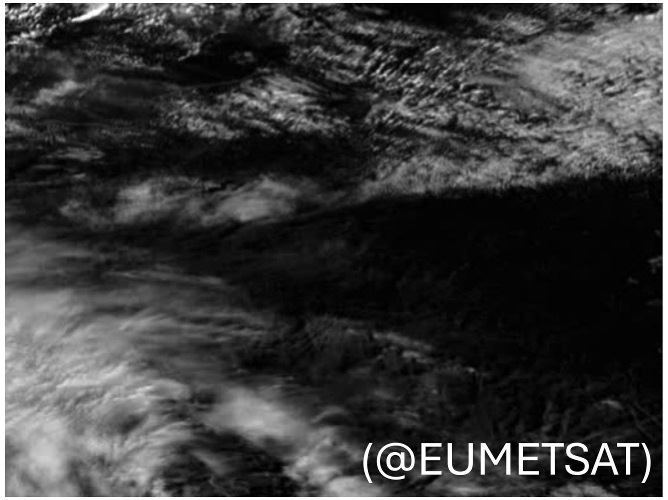
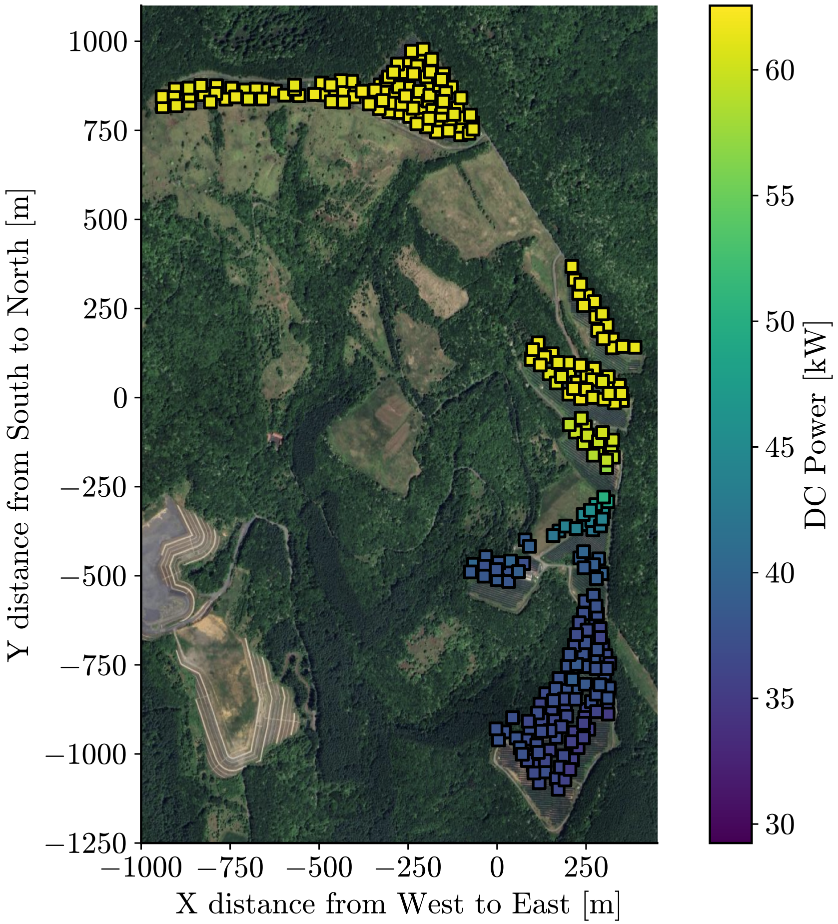
Context: Solar irradiance variability

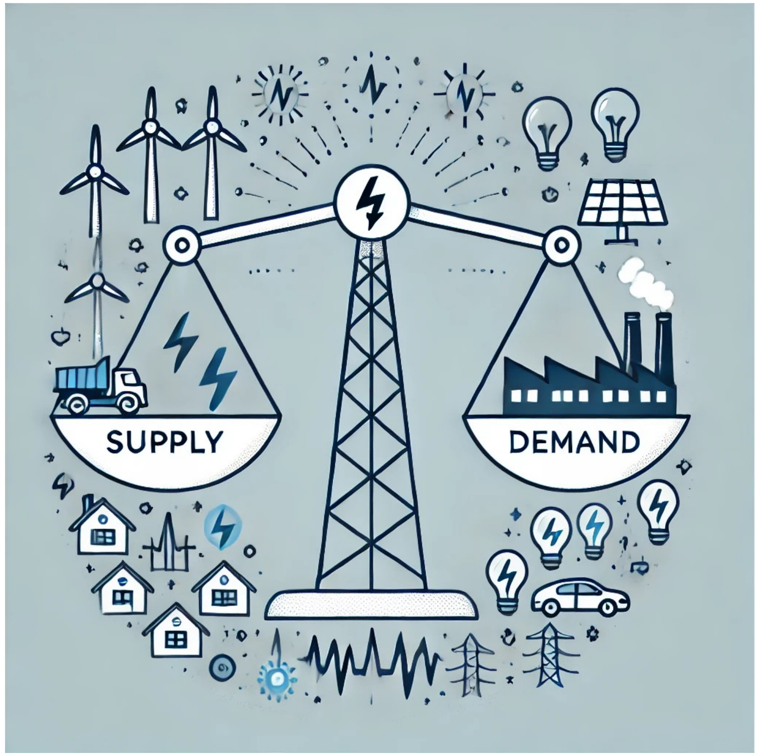
Meteorological factors



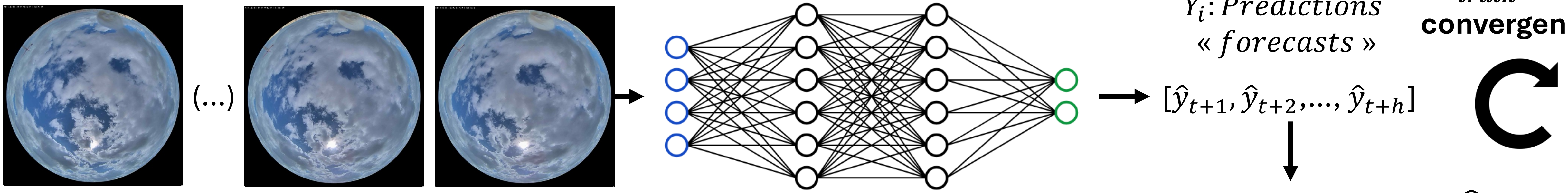
Variability of surface solar irradiance (SSI) and PV power production (ex. 25 MW)



Accurate solar forecasting for **supply-demand balance** and **grid stability**



Background: Data-driven solar forecasting



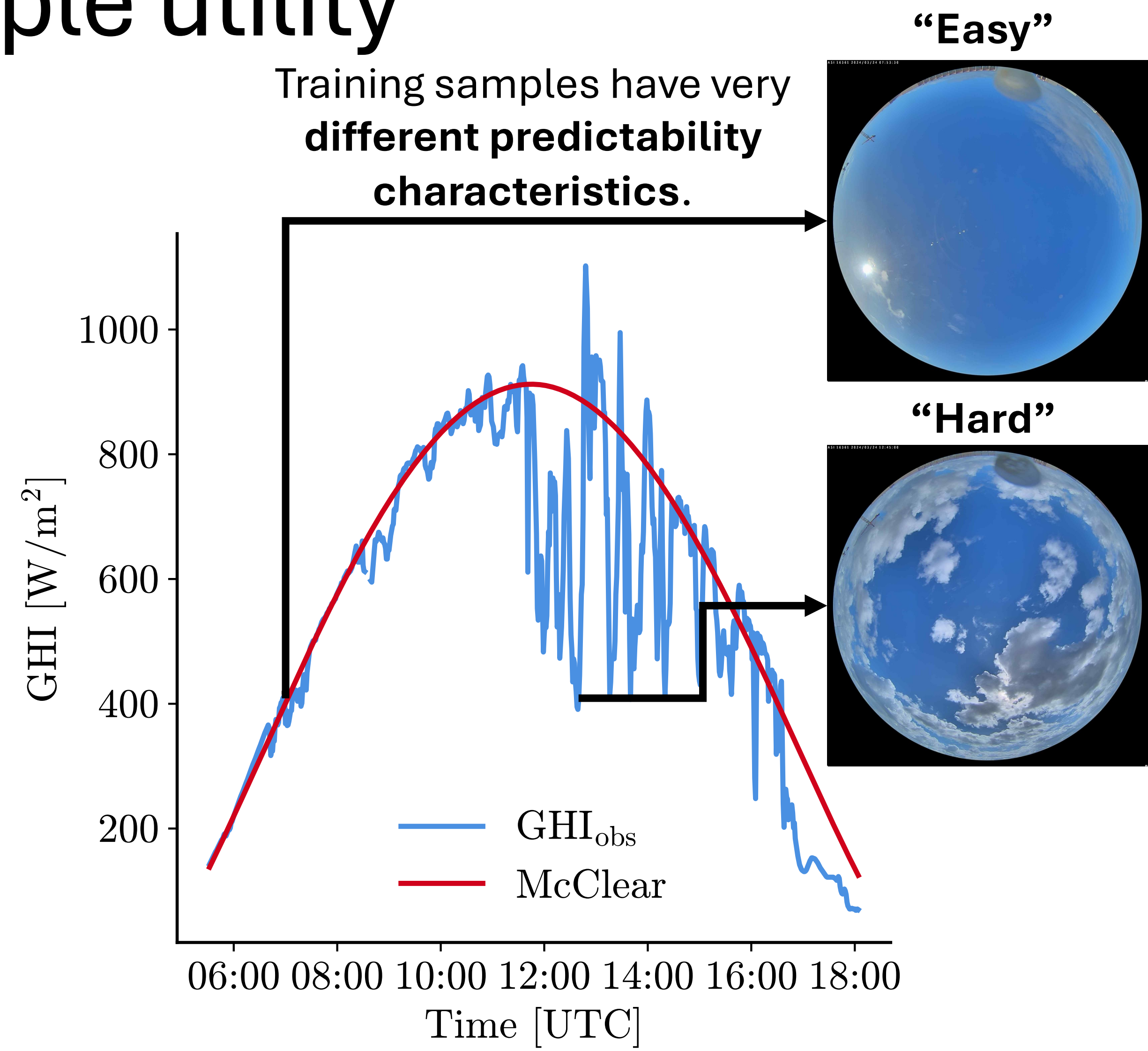
Deep learning model development process for **a single training sample (X_i, Y_i)**

- $D_{train} = \{(X_i, Y_i)\}_{i=1}^{N}$ represents the training dataset, used to optimize the model's parameters during the learning process.
- N is typically very large, ranging from **10^6 to 10^8**, representing years of on-site data acquisition.
- **General rule**: More data leads to better model performance.

Motivation: Training sample utility

Research questions:

- How can the relevance of training samples be evaluated?
- What is the optimal sampling strategy?
- What training resources can be conserved?

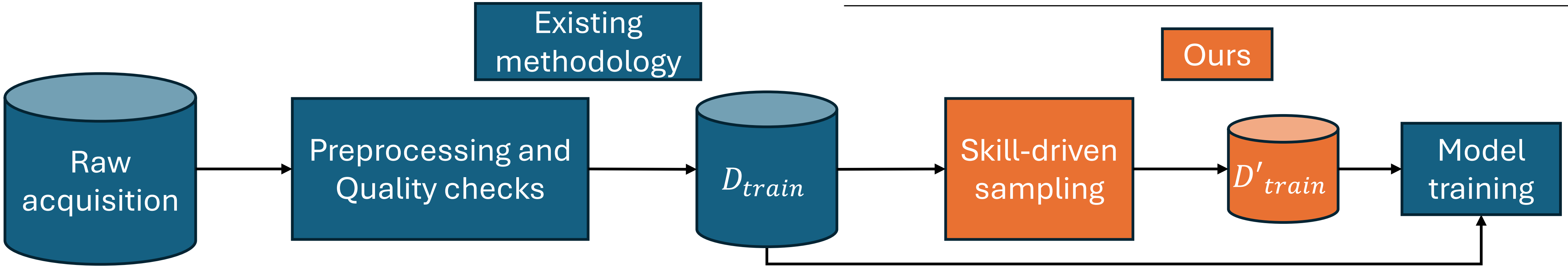


Proposal: Skill-driven sampling strategy

- We proposed to score the different training samples $\{(X_i, Y_i)\}_{i=1}^{N}$ using the **clear sky index persistence error:**
  - $\varepsilon_{persistence}(h) = |k_{t+h} - k_t|$
  - $k_t = \frac{GHI_{obs}}{GHI_{clear}}$
- $S = 1 - \frac{E_{model}}{E_{persistence}}$

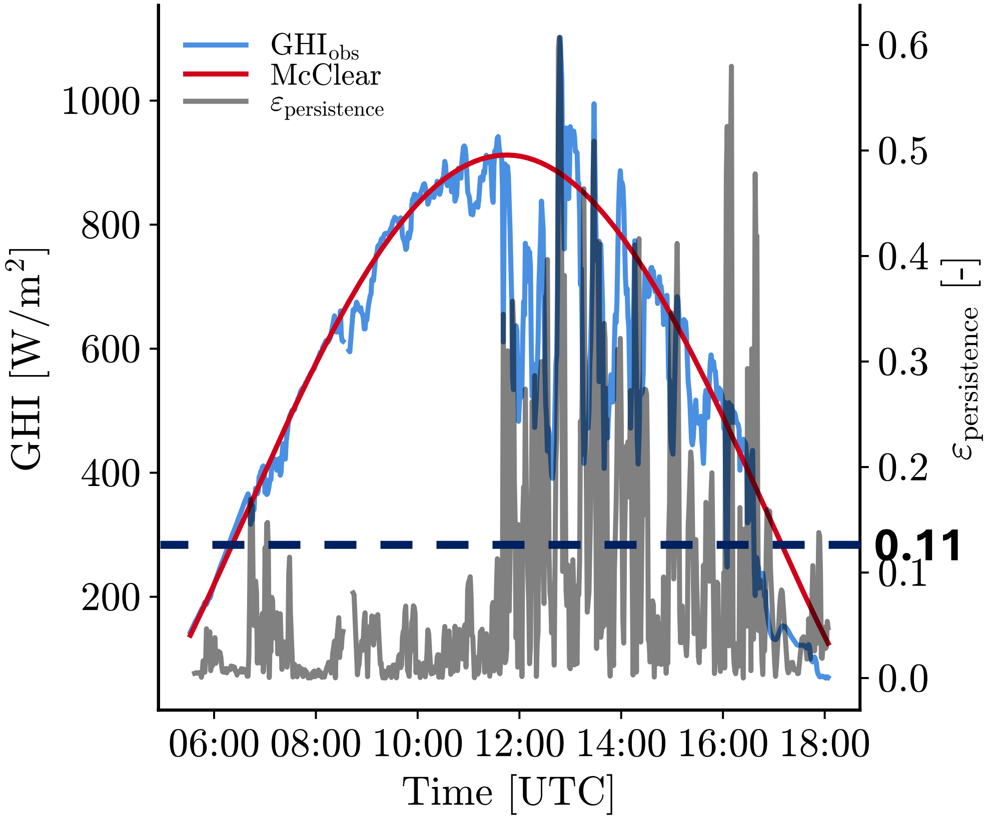
Algorithm 1 Skill-Driven Sampling

```
Input: D_train, forecasting horizon h, error threshold τ,
Output: D'_train
Initialize D'_train to an empty set
for each (x_i, y_i) ∈ D_train do
    Compute ε_persistence(h)
    if ε_persistence(h) > τ then
        Add (x_i, y_i) to D'_train
    end if
end for
return D'_train
```

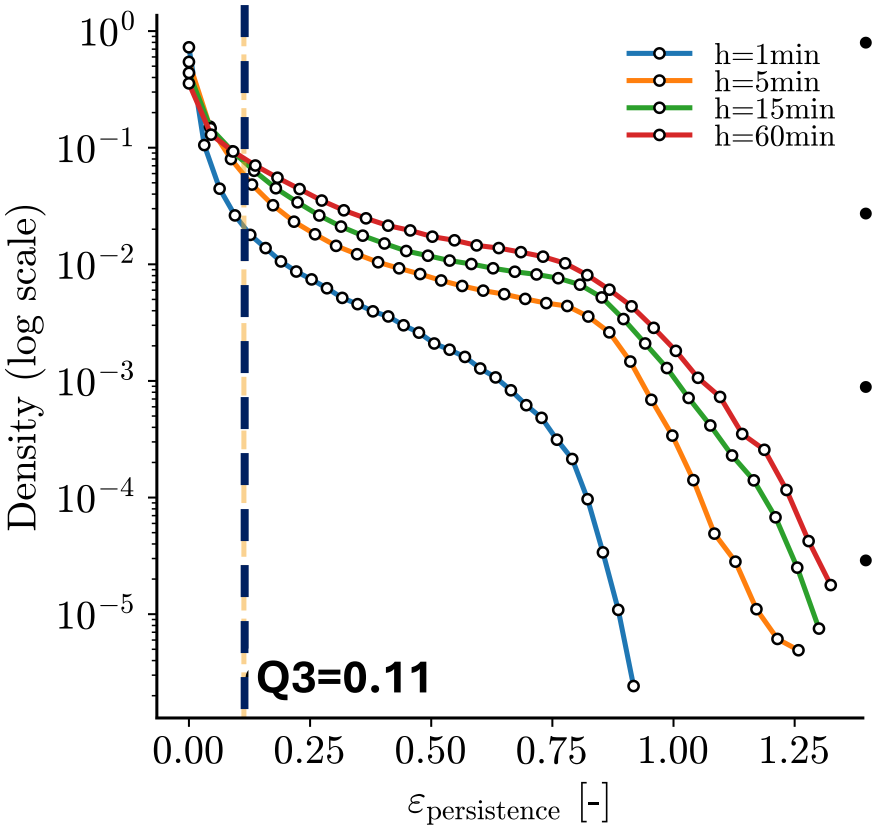


Example: Skill-driven sampling strategy

Sample information based on clear sky index persistence error (h=5min)



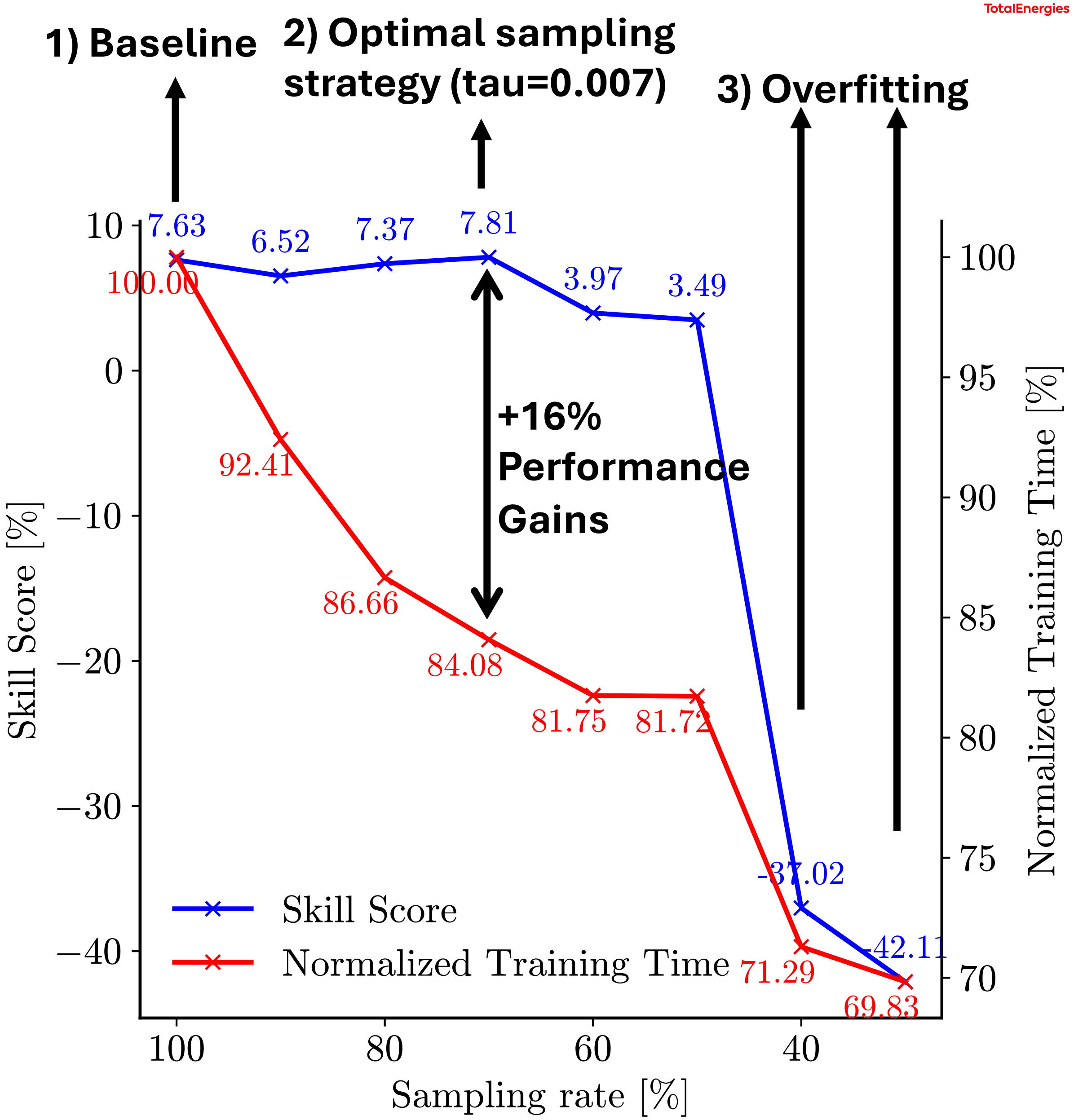
BSRN PAL - GHI 60s mean (2019-01-01 → 2022-12-31)



- Majority of samples show persistent clear sky index behaviors.
- High persistence performance typically leads to low skill score.
- Computational resources potentially wasted on uninformative data.
- But also, in BOS (Q3=0.08), RUN (Q3=0.11), and IZA (Q3=0.02)

Validation

- **Testing site:**
  - La Tour-de-Salvagny (near Lyon, France)
- **Hardware:**
  - Visible sky imager
  - Class A pyranometer (GHI)
- **Model:**
  - CNN-based neural network (28M parameters)
  - Forecasting horizon: 5min
- **Validation:**
  - Jul 2019 → Jul 2023
  - 60-second resolution
  - After preprocessing and quality checks, 324991 testing samples (10-fold cross-validation)
- **Conclusion:**
  - The skill-driven sampling strategy identified that **30% of the training data did not contribute to model improvement.**
  - Refining the dataset enabled a **16% reduction in training time compared to the baseline.**



Key takeaways

- When developing data-driven systems for solar forecasting tasks, a considerable amount of data may turn out to be uninformative for the model, leading to a slowdown in its development.
- The persistence error, based on the clear sky index, serves as a relevant proxy to estimate sample training utility for very short-term solar forecasting tasks.
- Our skill-driven sampling strategy reduced the dataset size by 30% and lowered computational resource requirements by 16% compared to the existing methodology.
- This gain in computational resource will be particularly valuable for the development of multi-site models and online learning.

Thank you for your attention!

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- www.eupvsec-proceedings.com:
  - **Short-paper**
  - **Slides**
- Extended manuscript under review at *Solar RRL*.

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PhD Student (O.I.E. – Mines Paris – PSL & TotalEnergies)
Topics: Spatial-temporal variability of irradiance, image-based solar forecasting, cloud characterization, geographic generalization, data-driven methods and PV power production application

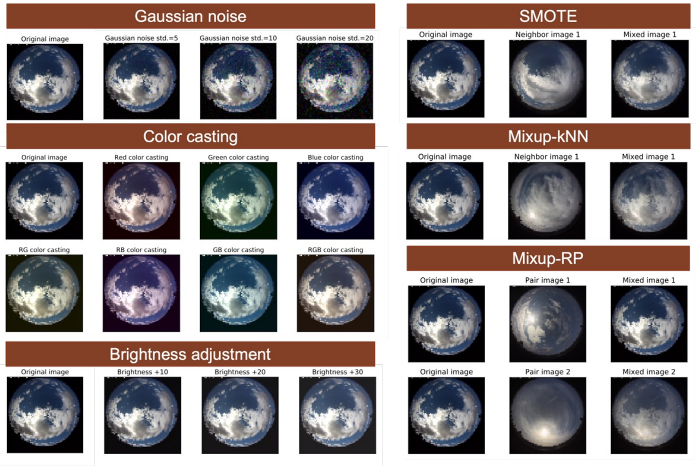
Data-centric methods for data-driven solar forecasting systems: Related work

- Nie, Yuhao, Ahmed S. Zamzam, and Adam Brandt. "Resampling and data augmentation for short-term PV output prediction based on an imbalanced sky images dataset using convolutional neural networks." Solar Energy 224 (2021): 341-354.
- Paletta, Quentin, Guillaume Arbod, and Joan Lasenby. "Cloud flow centring in sky and satellite images for deep solar forecasting." WCPEC-8. 2022. 5.
- Paletta, Quentin, et al. "SPIN: Simplifying Polar Invariance for Neural networks Application to vision-based irradiance forecasting." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2022.
- Liu, Ling-Man, et al. "Dual-dimension Time-GGAN data augmentation method for improving the performance of deep learning models for PV power forecasting." Energy Reports 9 (2023): 6419-6433.
- Fabel, Yann, et al. "Combining Deep Learning and Physical Models: A Benchmark Study on All-Sky Imager-Based Solar Nowcasting Systems." Solar RRL 8.4 (2024): 2300808.

Perspectives

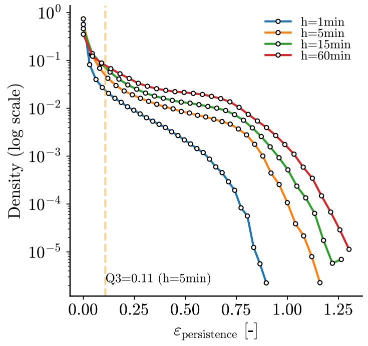
- Combining skill-driven sampling with data augmentation methods to limit small dataset problems.

Nie et al., Solar Energy, 2021



Paletta et al., CVPR, 2022

- We found experimentally that tau=0.007 was the optimal training threshold based on one location.
- While we expect to remain applicable to other datasets, it needs to be demonstrated.



Ex. BSRN RUN (2019-01-01 → 2023-12-31)

- Similar $\varepsilon_{persistence}$ distribution to BSRN PAL.

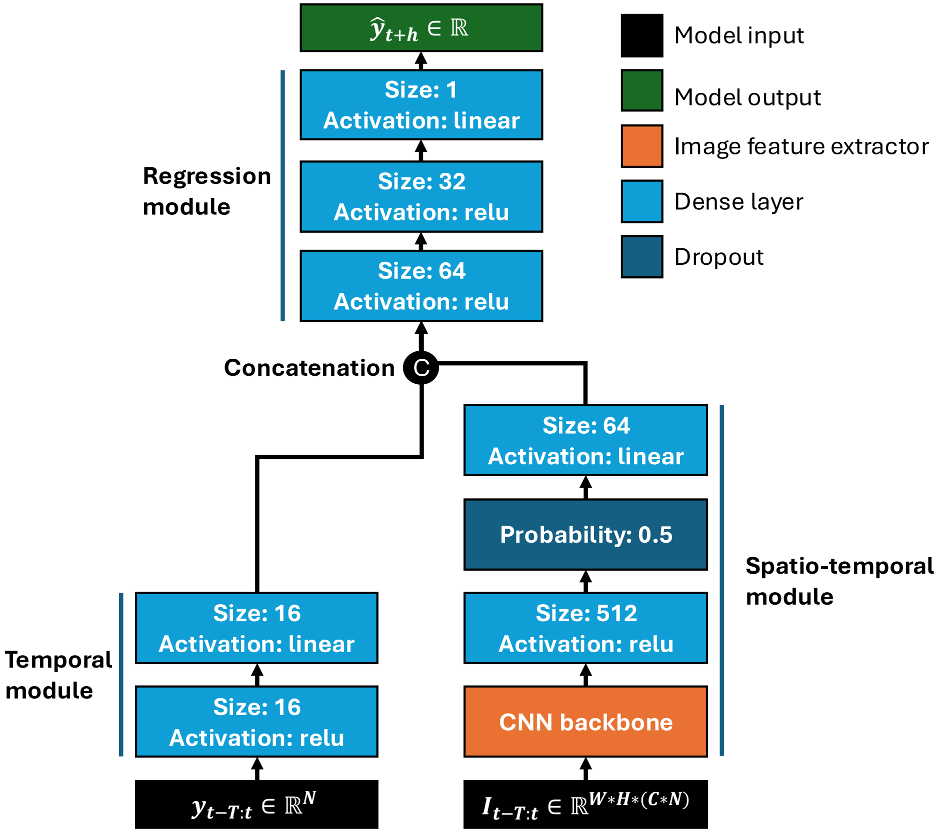
Methodology

Testing site

Pyranometer (GHI)
Reference Measurements

Sky imager

Model architecture overview



Model performance assessment

Model	↓ MBE Wm^{-2} (%)	↓ MAE Wm^{-2} (%)	↓ RMSE Wm^{-2} (%)	↑ RMSE Skill Score %
10-fold Cross-validation (from 2019-07-09 to 2023-06-01)				
Ours	0.10 (0.02)	38.10 (9.63)	85.84 (21.70)	7.63
Observation Mean: 395.54 Wm^{-2} – Observation Number: 324991				
Visible commercial solution (from 2020-09-01 to 2020-11-08)				
Visible	6.35 (1.99)	49.48 (15.52)	89.96 (28.21)	-11.20
Ours	-1.24 (-0.39)	35.30 (11.07)	72.86 (22.85)	9.94
Observation Mean: 318.89 Wm^{-2} – Observation Number: 6872				
Infrared commercial solution (from 2022-11-15 to 2023-03-06)				
Infrared	12.92 (5.46)	34.09 (14.40)	71.81 (30.32)	-28.75
Ours	0.21 (0.09)	27.20 (11.48)	52.37 (22.11)	6.11
Observation Mean: 236.84 Wm^{-2} – Observation Number: 7835				

Our model vs.
Actual GHI observations

Our model vs.
Commercial solution A vs.
actual GHI observations

Our model vs.
Commercial solution B vs.
actual GHI observations

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Skill-driven sampling validation

τ (%)	$\downarrow$ MBE Wm^{-2} (%)	$\downarrow$ MAE Wm^{-2} (%)	$\downarrow$ RMSE Wm^{-2} (%)	$\uparrow$ RMSE Skill Score %	$\downarrow$ Normalized Training Time %
0.061 (30)	13.02 (3.29)	66.35 (16.77)	132.06 (33.39)	-42.11	69.83
0.038 (40)	3.48 (0.88)	50.64 (12.80)	127.34 (32.19)	-37.02	71.29
0.023 (50)	3.04 (0.77)	43.85 (11.09)	89.68 (22.67)	3.49	81.72
0.014 (60)	2.61 (0.66)	41.19 (10.41)	89.24 (22.56)	3.97	81.75
0.007 (70)	3.37 (0.85)	39.51 (9.99)	85.67 (21.66)	7.81	84.08
0.004 (80)	1.13 (0.28)	38.82 (9.81)	86.08 (21.76)	7.37	86.66
0.002 (90)	0.64 (0.16)	38.85 (9.82)	86.87 (21.96)	6.52	92.41
0.000 (100)	0.10 (0.02)	38.10 (9.63)	85.84 (21.70)	7.63	100
Observation Mean: 395.54 Wm^{-2} – Observation Number: 324991					