Photovoltaic prediction from sky image sequences

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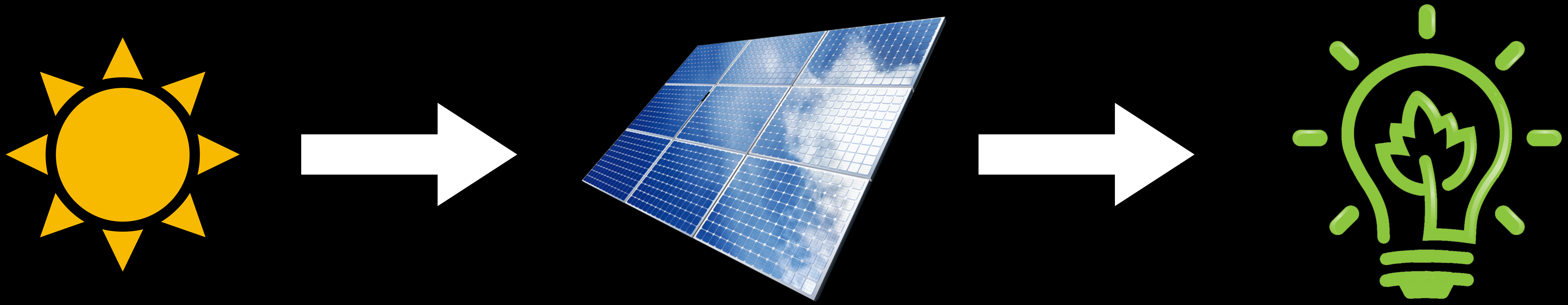
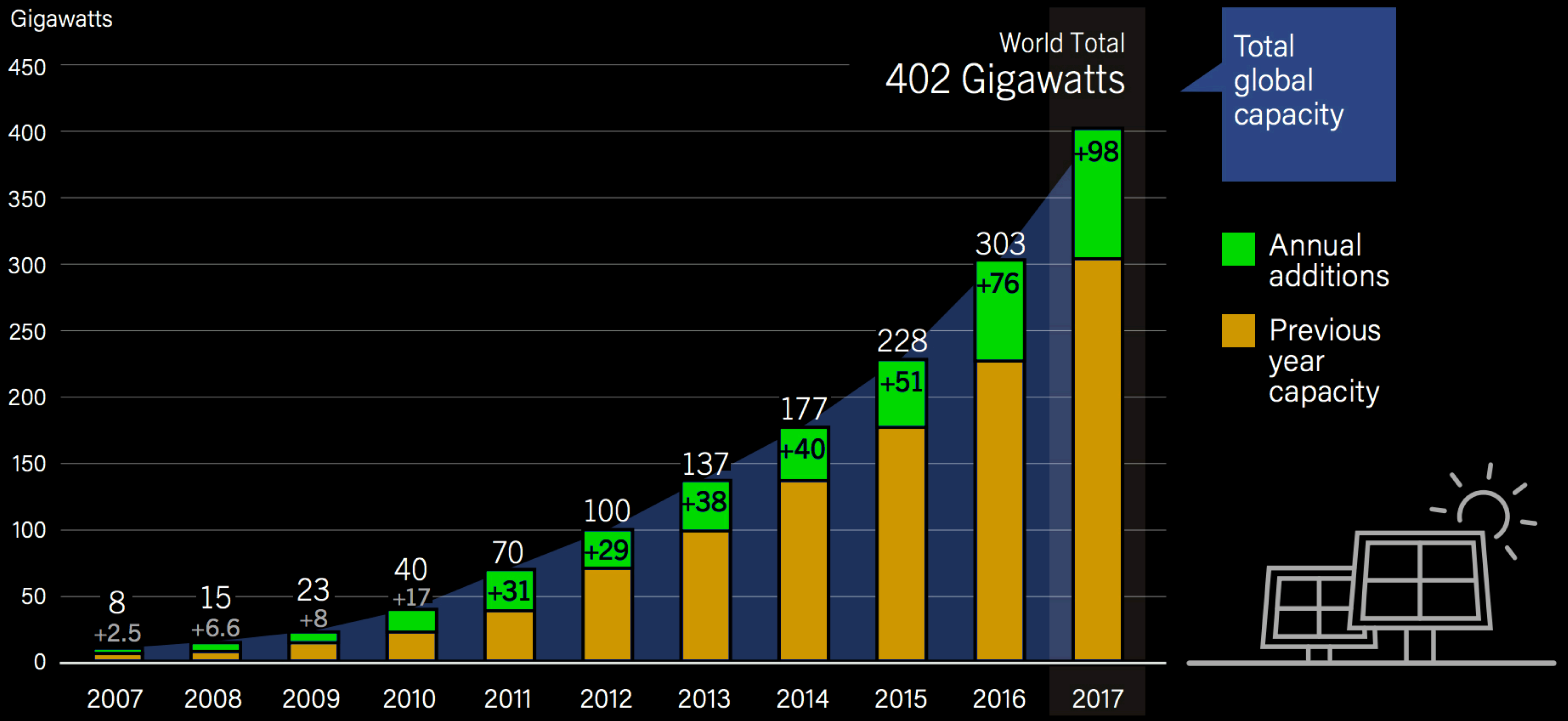
Universidad de O’Higgins, Chile

Solar energy



Photovoltaic panel

Solar energy global capacity, 2007-2017

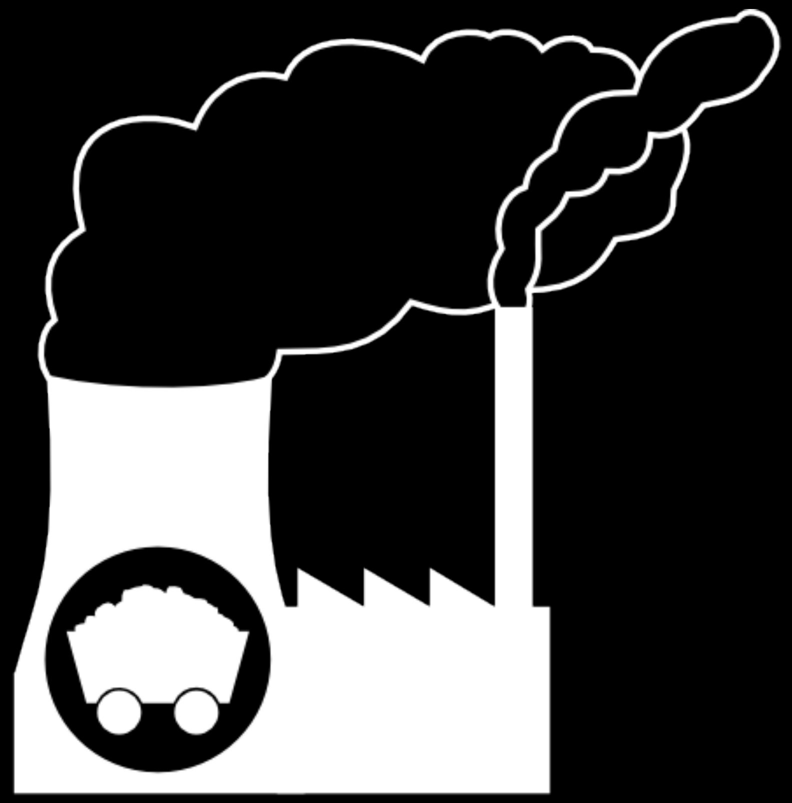


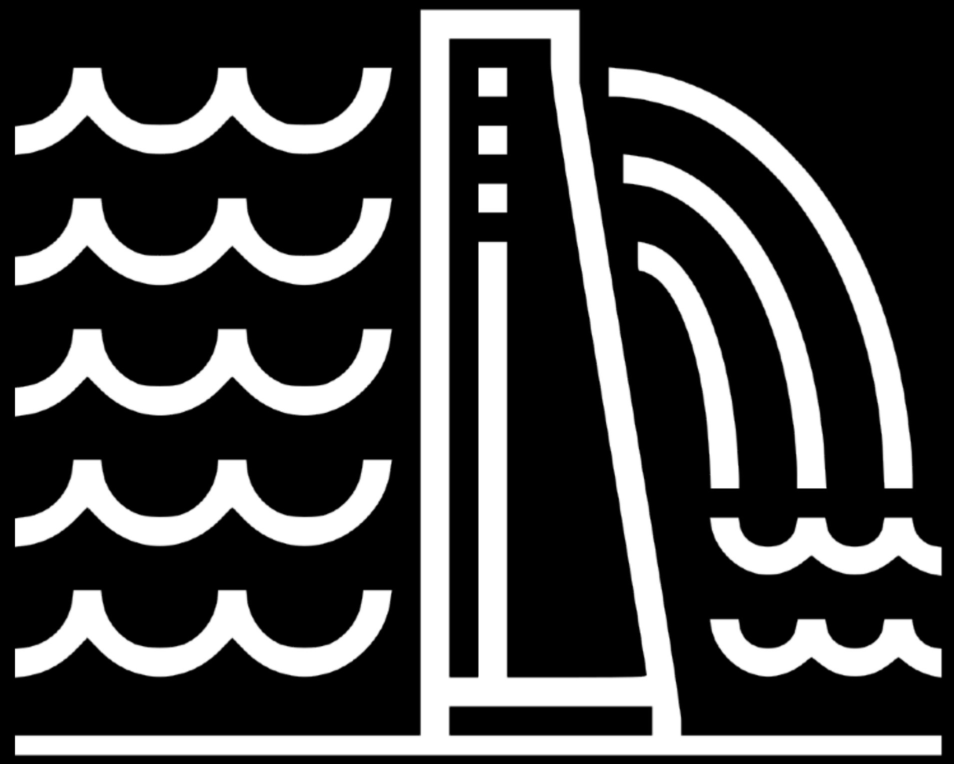
40,000 solar panels were installed each hour of the year

Source: RENEWABLES 2018 GLOBAL STATUS REPORT

Solar energy v.s. “traditional” energy

Traditional energy

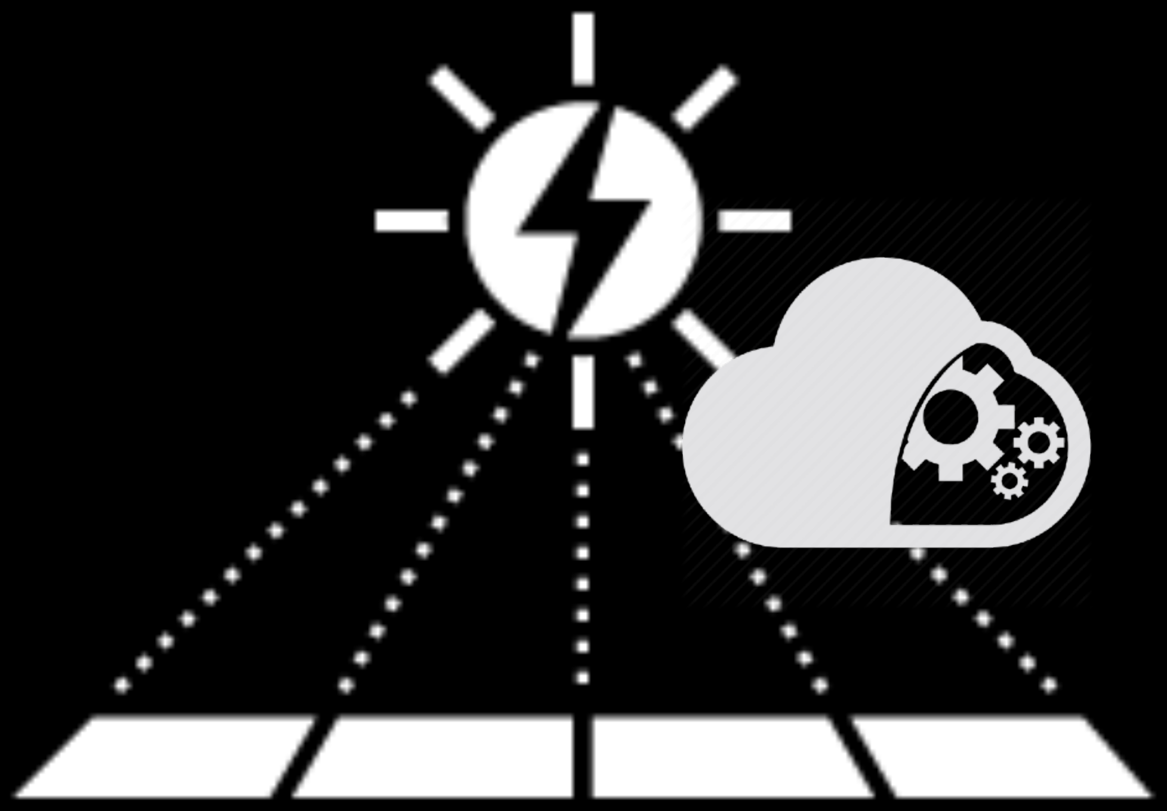

Coal power plant


Hydropower plant


Nuclear power plant

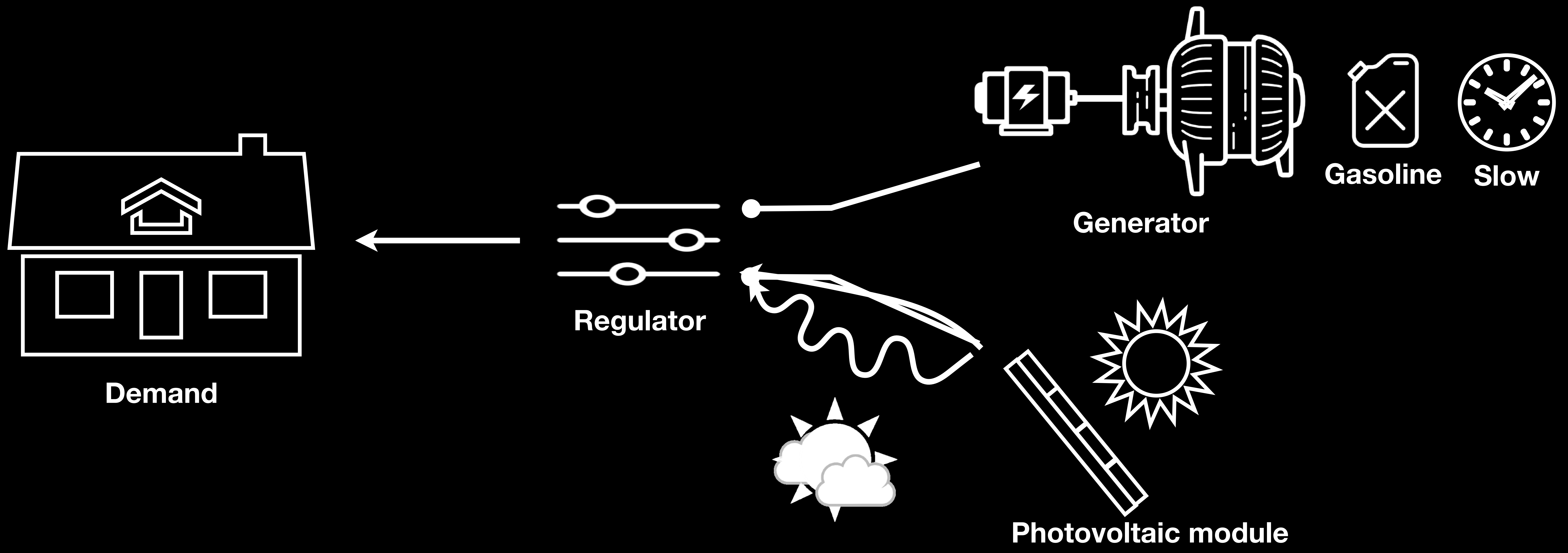
Controllable

Solar energy


Photovoltaic power station

Uncontrollable

Problem with solar energy

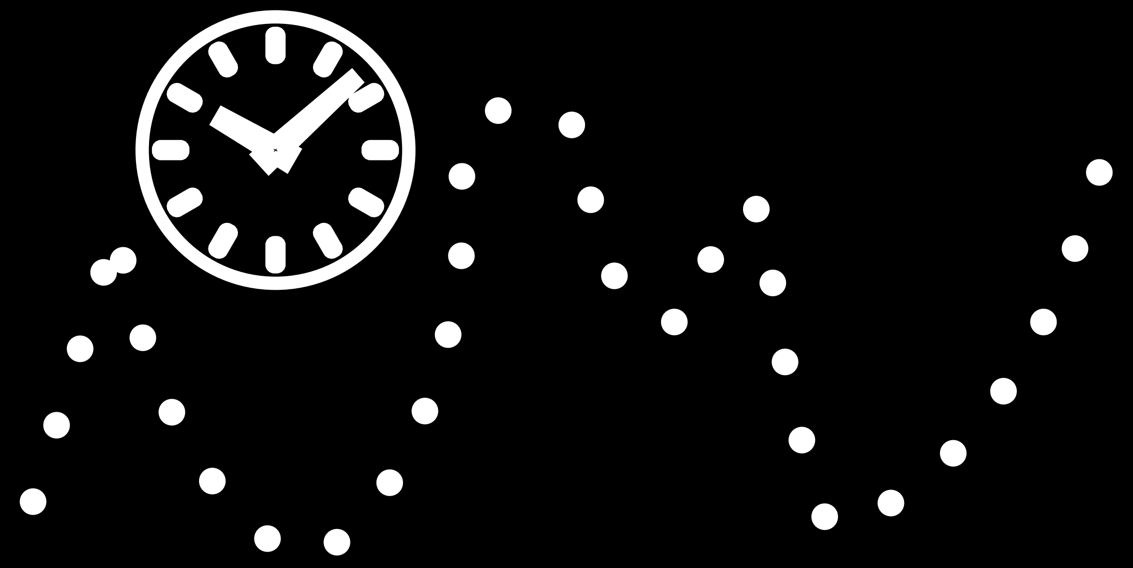


Forecasting future photovoltaic (PV) power at short time scales

Short time scale (minutes) = Nowcasting

Photovoltaic = PV

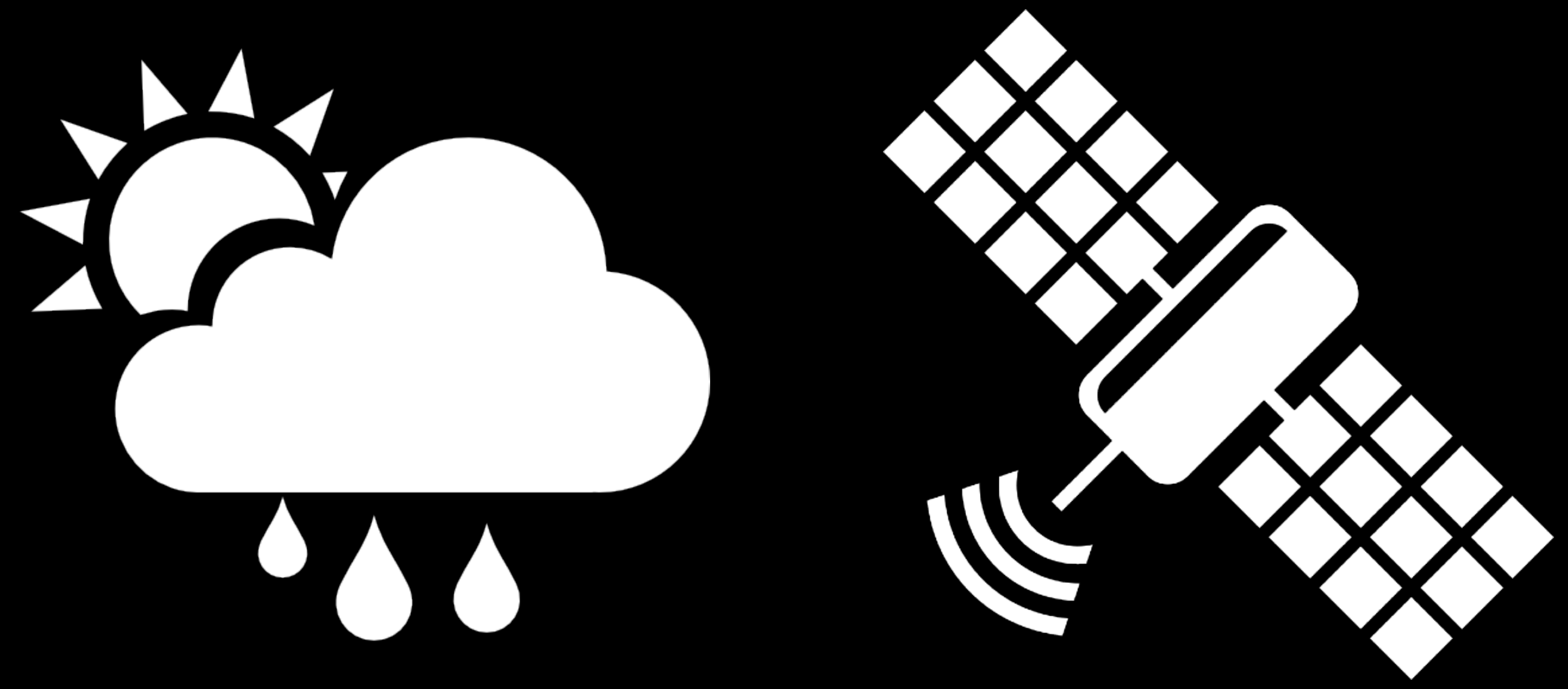
Data sources



Historical PV power

- Easy to obtain
- Location Dependent

✗



Weather stations & satellites

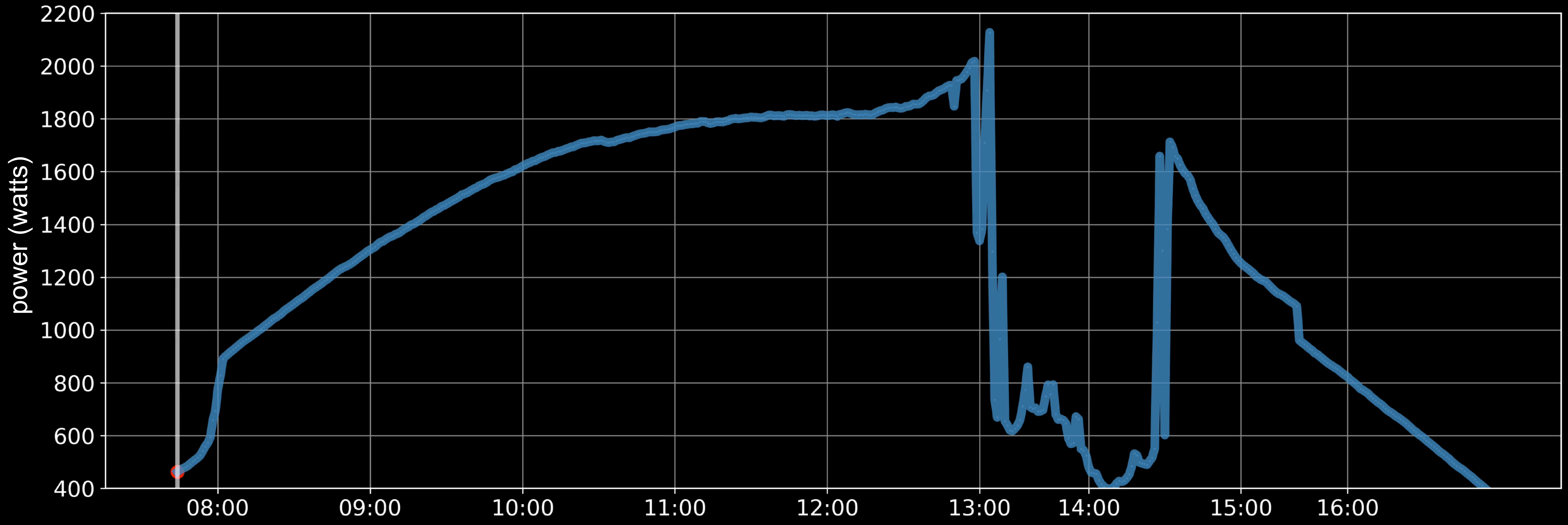
- Few and sparse, far
- Limited spatial & time resolution

✗

Camera

- Close to the panel
- High resolution

✓



power (watts)
2200
2000
1800
1600
1400
1200
1000
800
600
400
08:00
09:00
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11:00
12:00
13:00
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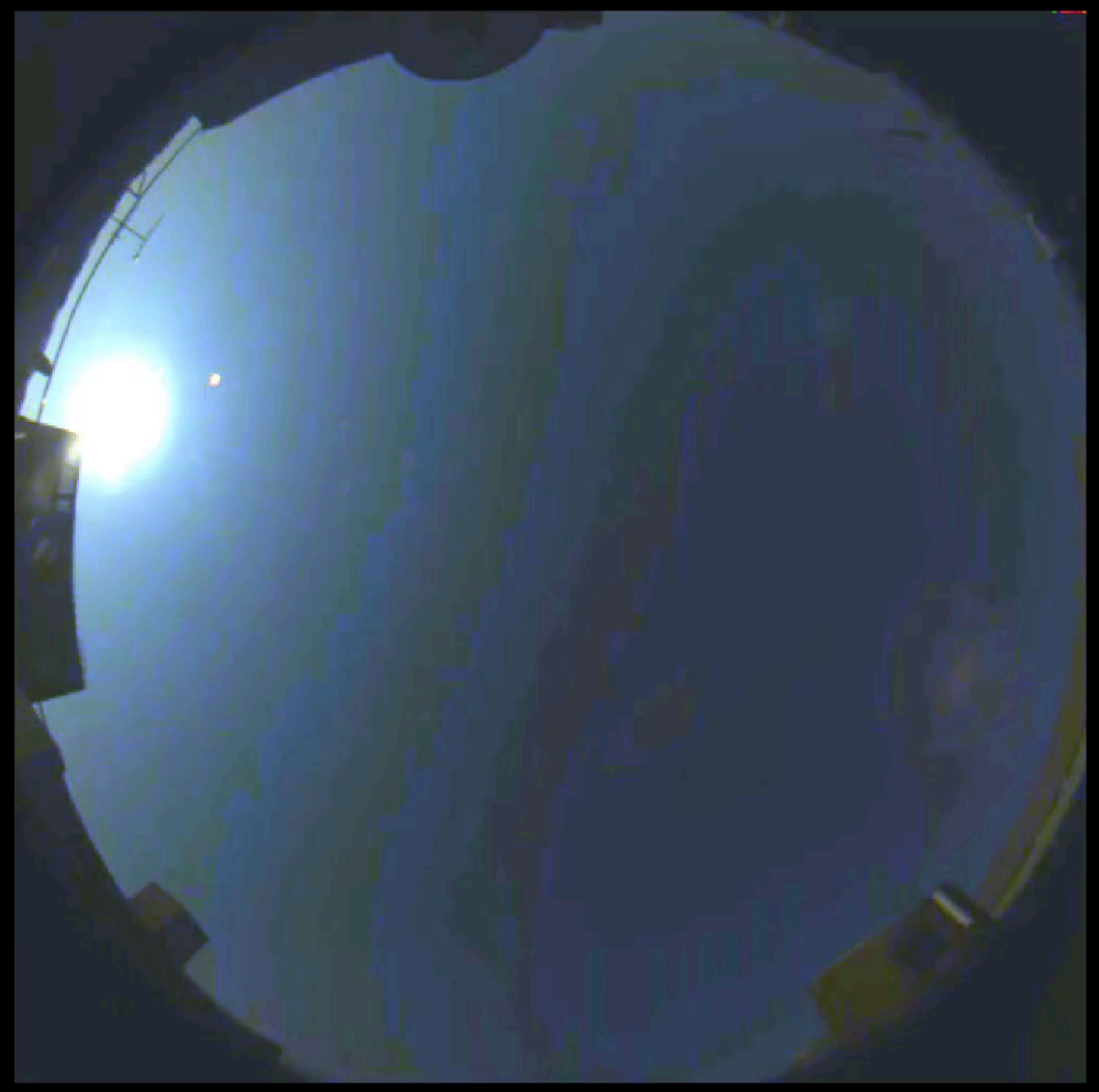
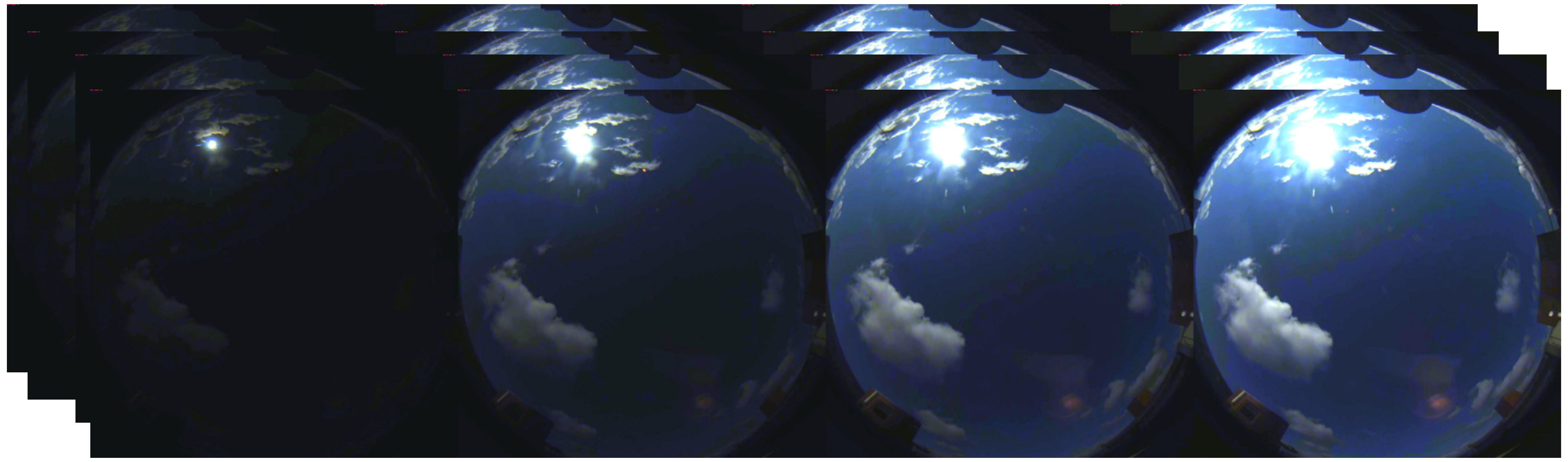
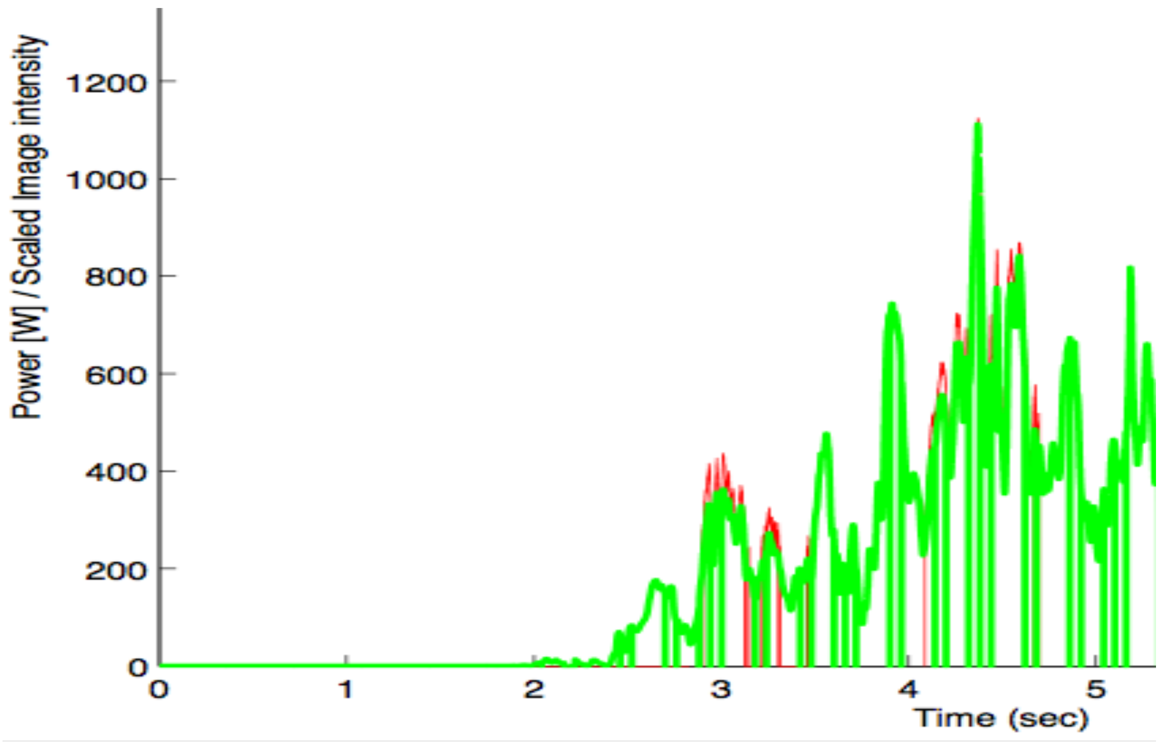


Input

- Sky Images



- PV history (few minutes)



Prediction models

No physical model

- Use only PV information:

$$\hat{p}_{t_0} = f(\mathbf{p}; \mathcal{W}) ,$$

$$\mathbf{p} = [p_{t_0-k}, \ldots, p_{t_0}]$$

- Use PV and Image information

$$\hat{p}_{t_0} = f(\mathbf{p}, \mathcal{I}; \mathcal{W})$$

$$\mathcal{I} = [\mathbf{I}_{t_0-k}, \ldots, \mathbf{I}_{t_0}]$$

- Use only Image information

$$\hat{p}_{t_0} = f(\mathcal{I}; \mathcal{W}) .$$

Deep Photovoltaic Nowcasting

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[†]Université Laval, Québec, Canada
[*]Universidad de O'Higgins, Chile
[*]Kyoto University, Kyoto, Japan

PV nowcasting: previous approaches

Sky images

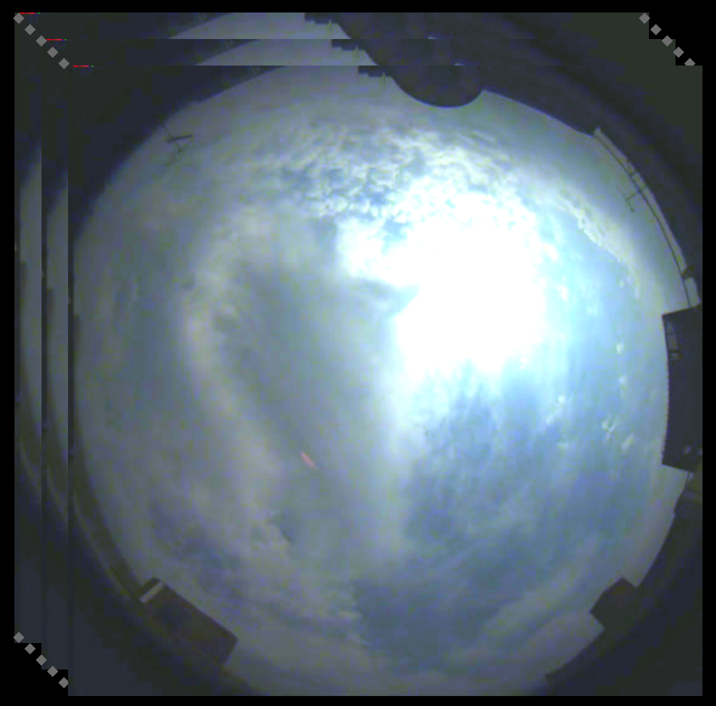
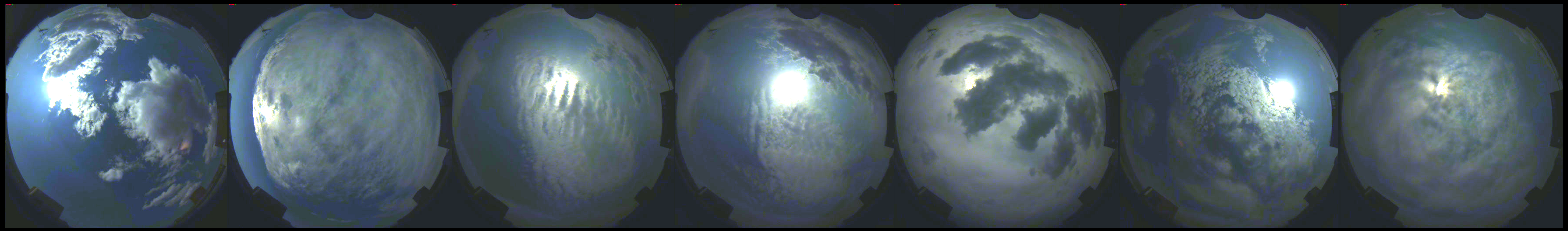


Image Processing

Prediction (Handcrafted features)

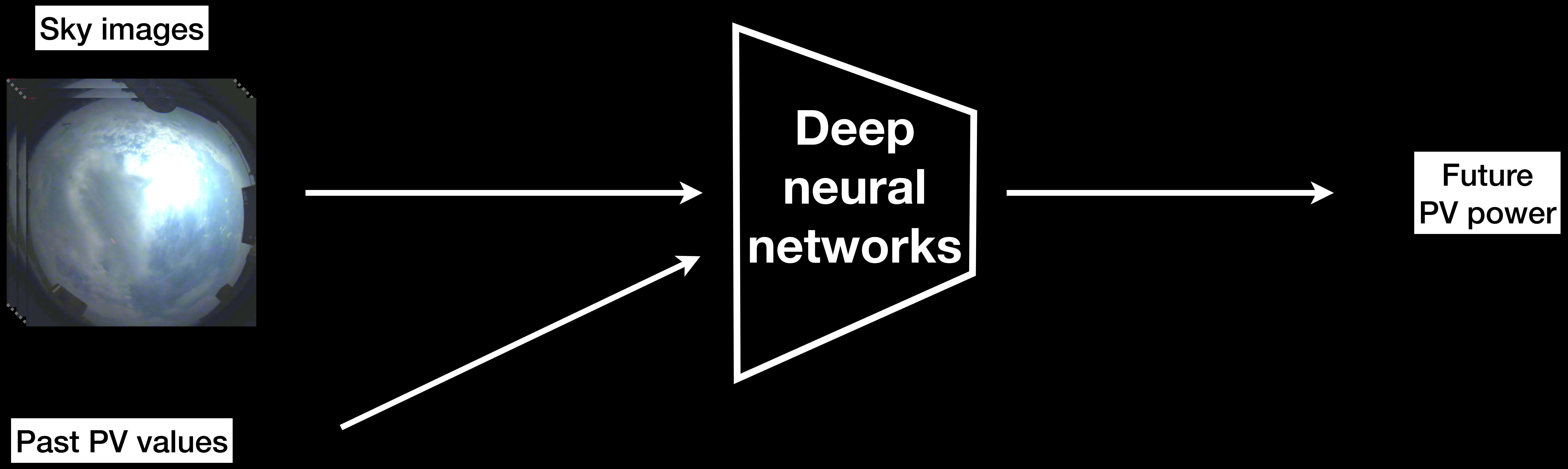
Future PV power

Past PV values



Chu Y, Urquhart B, Gohari SM, Pedro HT, Kleissl J, Coimbra CF. Short-term reforecasting of power output from a 48 MWe solar PV plant. Solar Energy. 2015
Peng Z, Yu D, Huang D, Heiser J, Yoo S, Kalb P. 3D cloud detection and tracking system for solar forecast using multiple sky imagers. Solar Energy. 2015
Taravat A, Del Frate F, Cornaro C, Vergari S. Neural networks and support vector machine algorithms for automatic cloud classification of whole-sky ground-based images. IEEE Geoscience and remote sensing letters. 2015

PV nowcasting: ours



Directly learn a mapping between past PV, past images and future PV power.

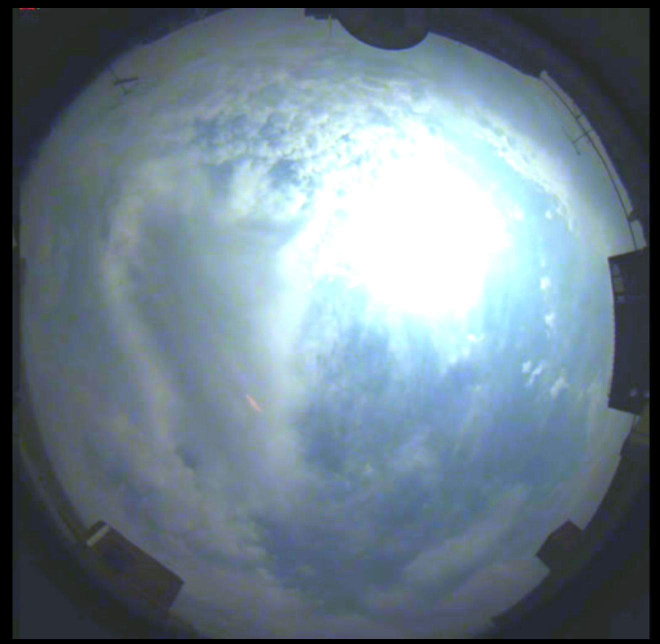
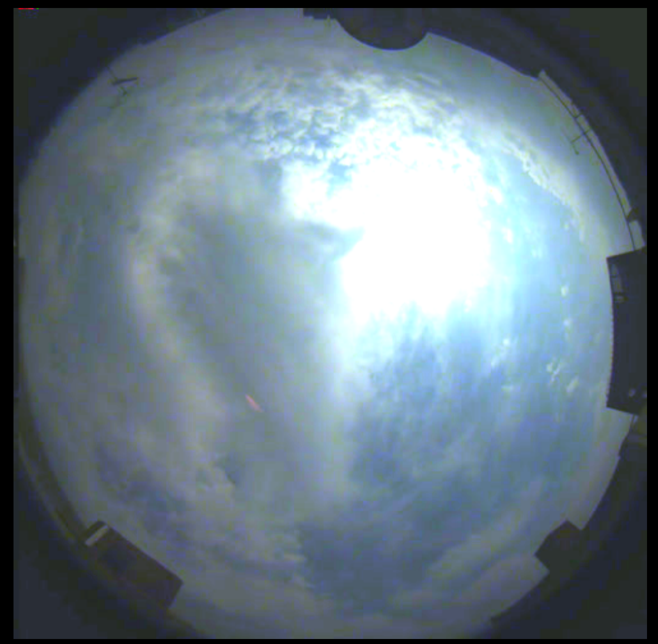
Contributions:

1. **Apply deep learning to the photovoltaic nowcasting problem**
2. **Present various architectures to predict the 1-minute future**
3. **Vastly outperforming the baseline model**

Outline

- **Problem setup & data**
- **Network structures for various inputs:**
  1. **PV power only**
  2. **PV power + image**
  3. **PV power + image + temporal information**
- **Evaluation**

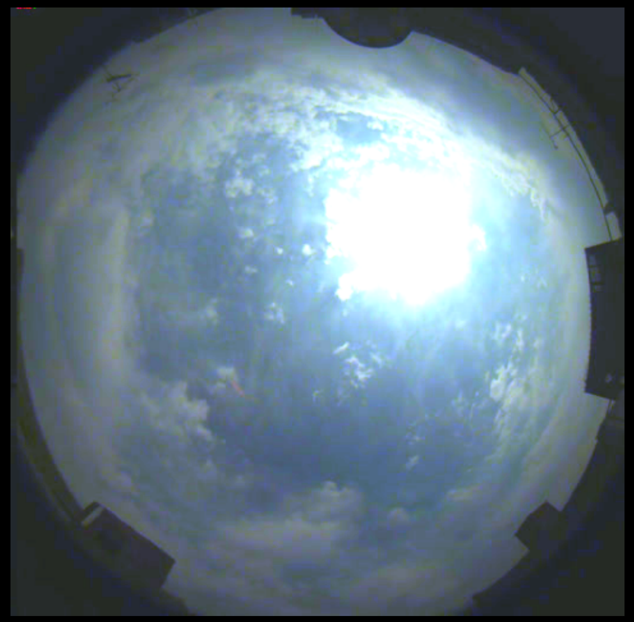
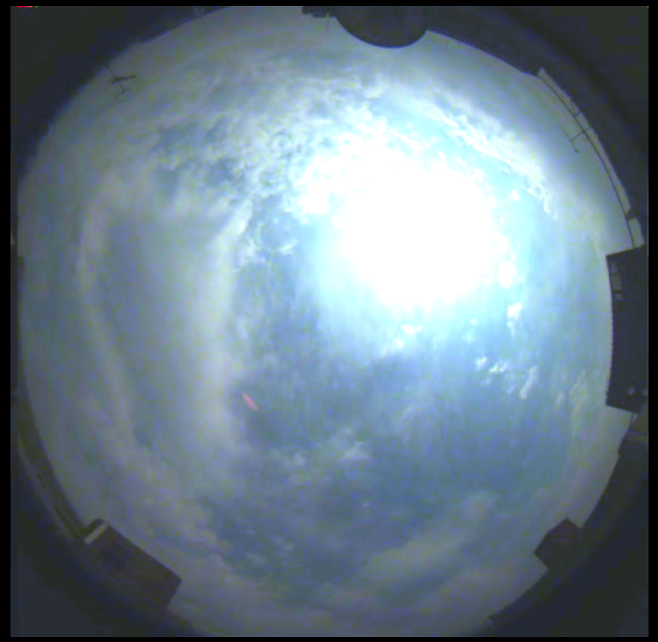
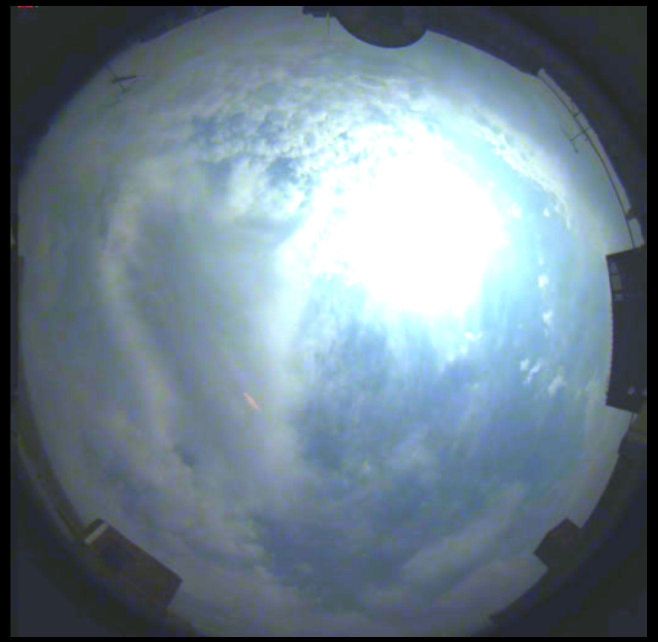
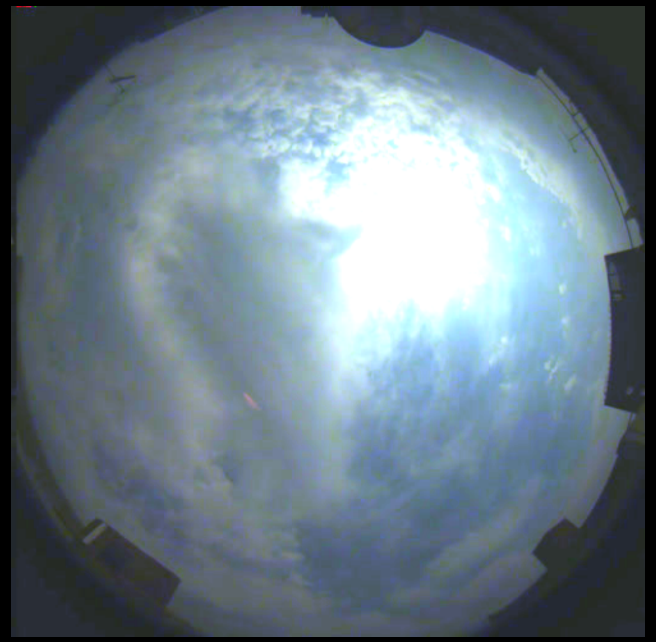
Problem setup

	Current	Future
Sky image		
PV power	p_t	p_{t+1}

$$\Delta p_t = p_{t+1} - p_t$$

$$\hat{p}_{t+1} = p_t + \Delta \hat{p}_t$$

Problem setup

	Past		Past	Current	Future
Sky image		• • •			
PV power	p_{t-5}		p_{t-1}	p_t	p_{t+1}

$$\Delta p_t = p_{t+1} - p_t$$

$$\hat{p}_{t+1} = p_t + \Delta \hat{p}_t$$

$$\mathcal{L}_{\Delta p_t} = ||\Delta \hat{p}_t - \Delta p_t||_2$$

Data: PV + Image

11ms 88ms 176ms 264ms

Four different exposure times


90 days over 6 months

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  2. PV power + image
  3. PV power + image + temporal information
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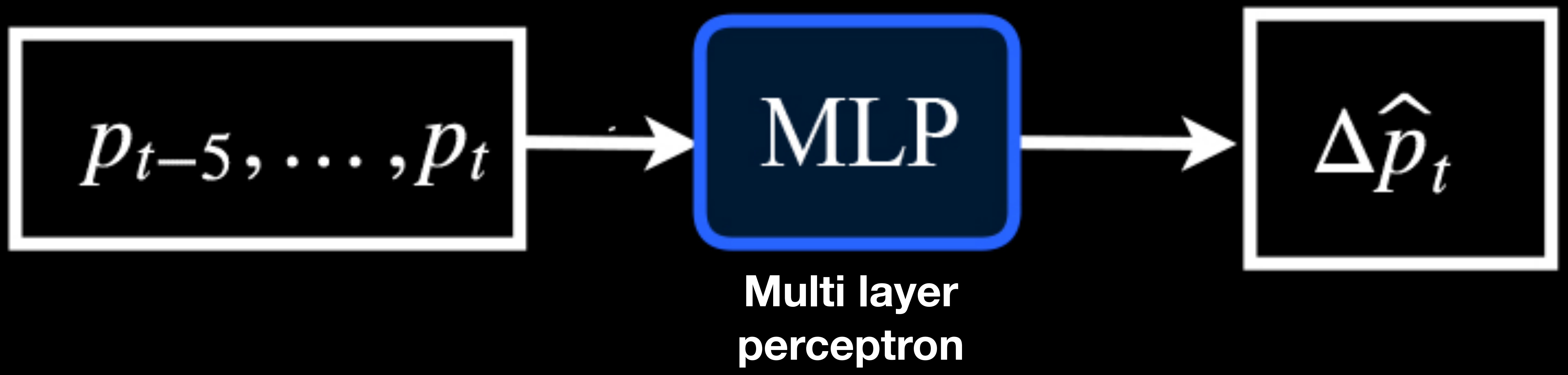
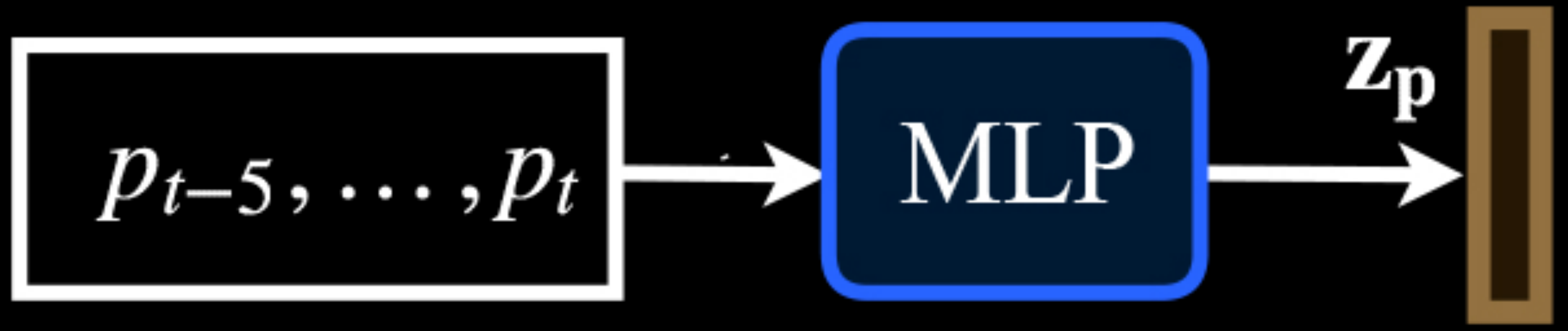
Power only



MLP Baseline

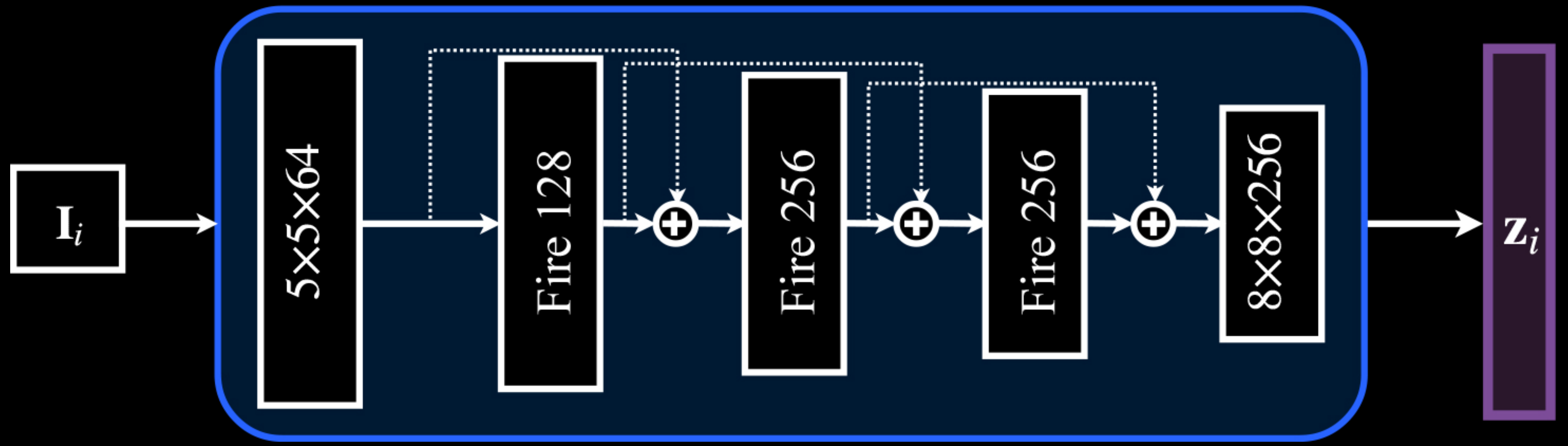
Rana M, Koprinska I, Agelidis VG. Univariate and multivariate methods for very short-term solar photovoltaic power forecasting. Energy Conversion and Management. 2016
Voyant C, Notton G, Kalogirou S, Nivet ML, Paoli C, Motte F, Fouilloy A. Machine learning methods for solar radiation forecasting: A review. Renewable Energy. 2017

Power + image

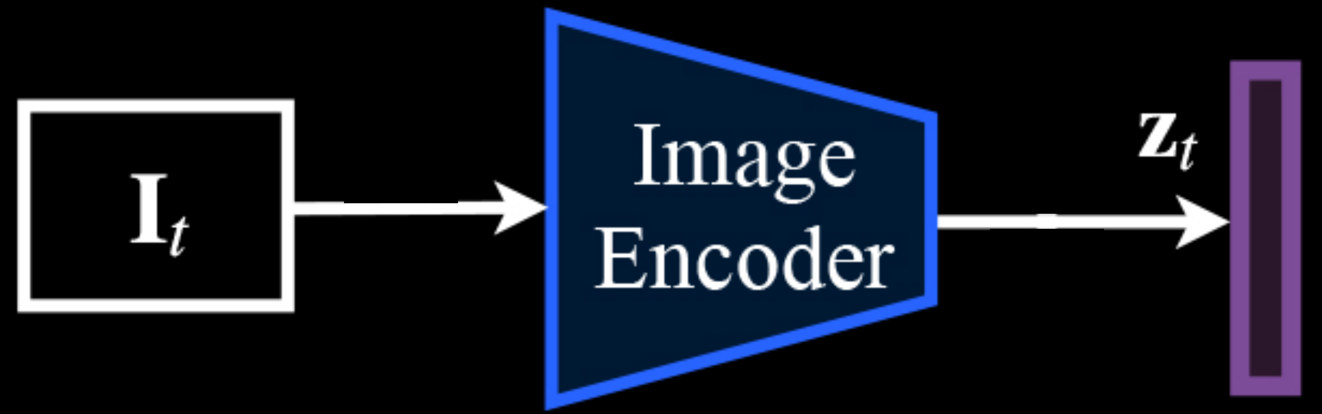


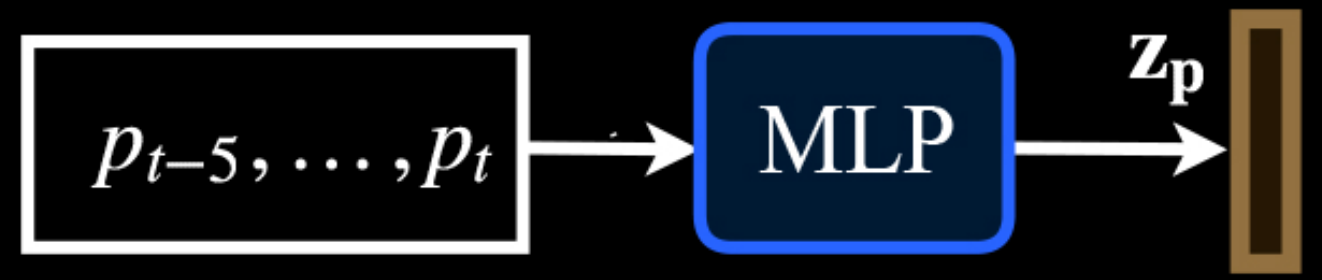
Power + image

Image Encoder

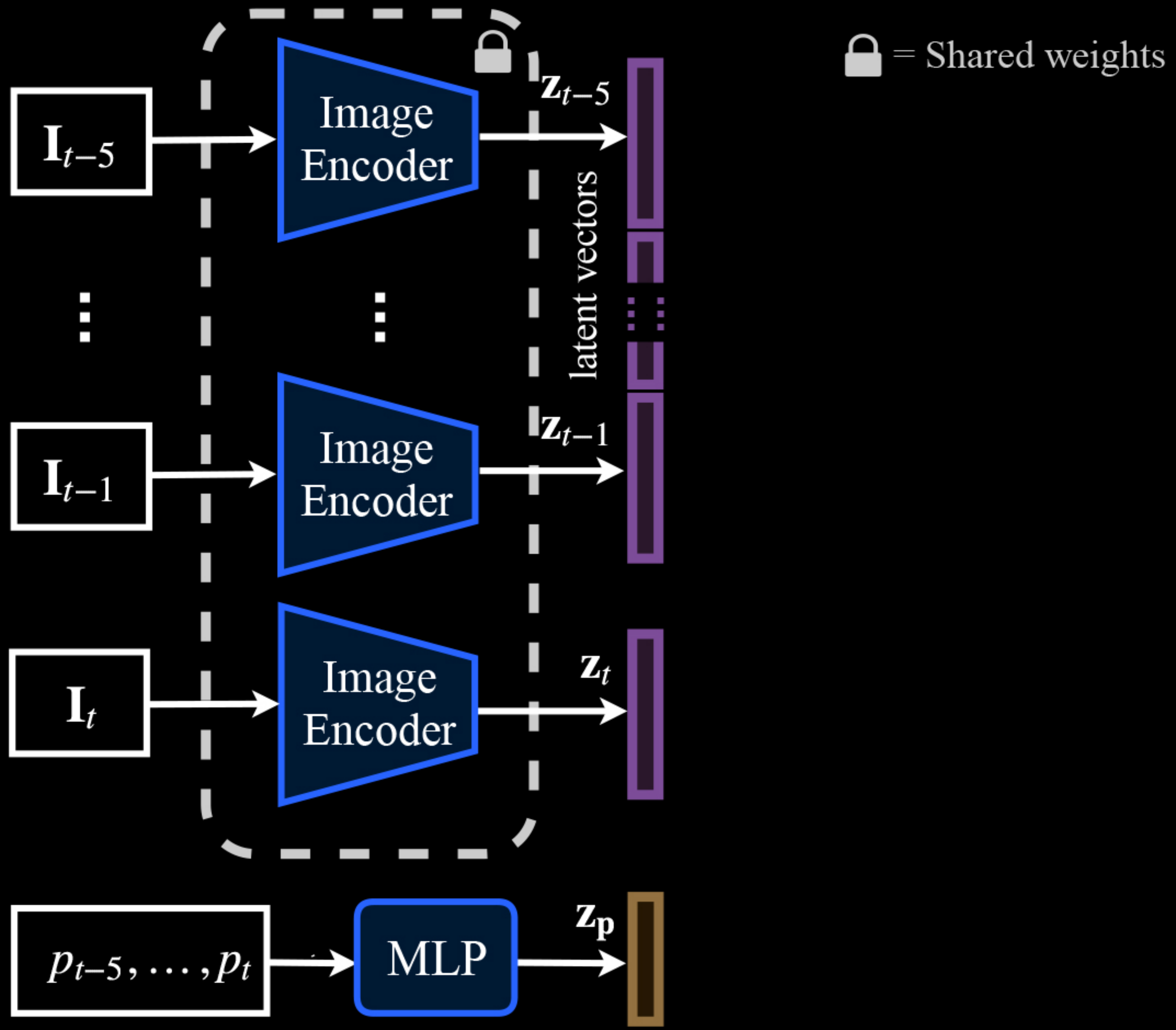


He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.
Iandola, Forrest N., et al. "Squeezenet: Alexnet-level accuracy with 50x fewer parameters and< 0.5 mb model size." arXiv preprint arXiv:1602.07360 (2016).



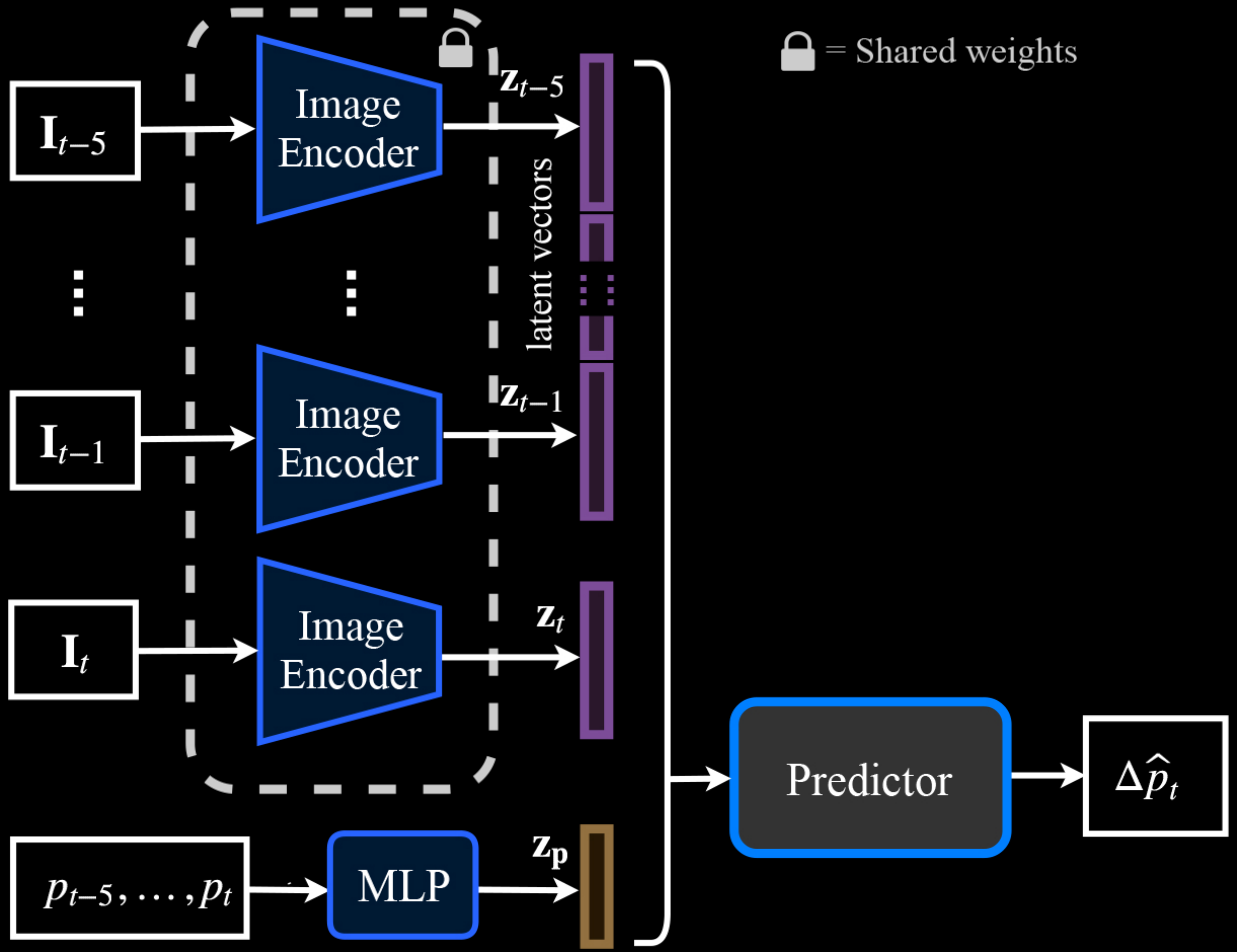


Power + image



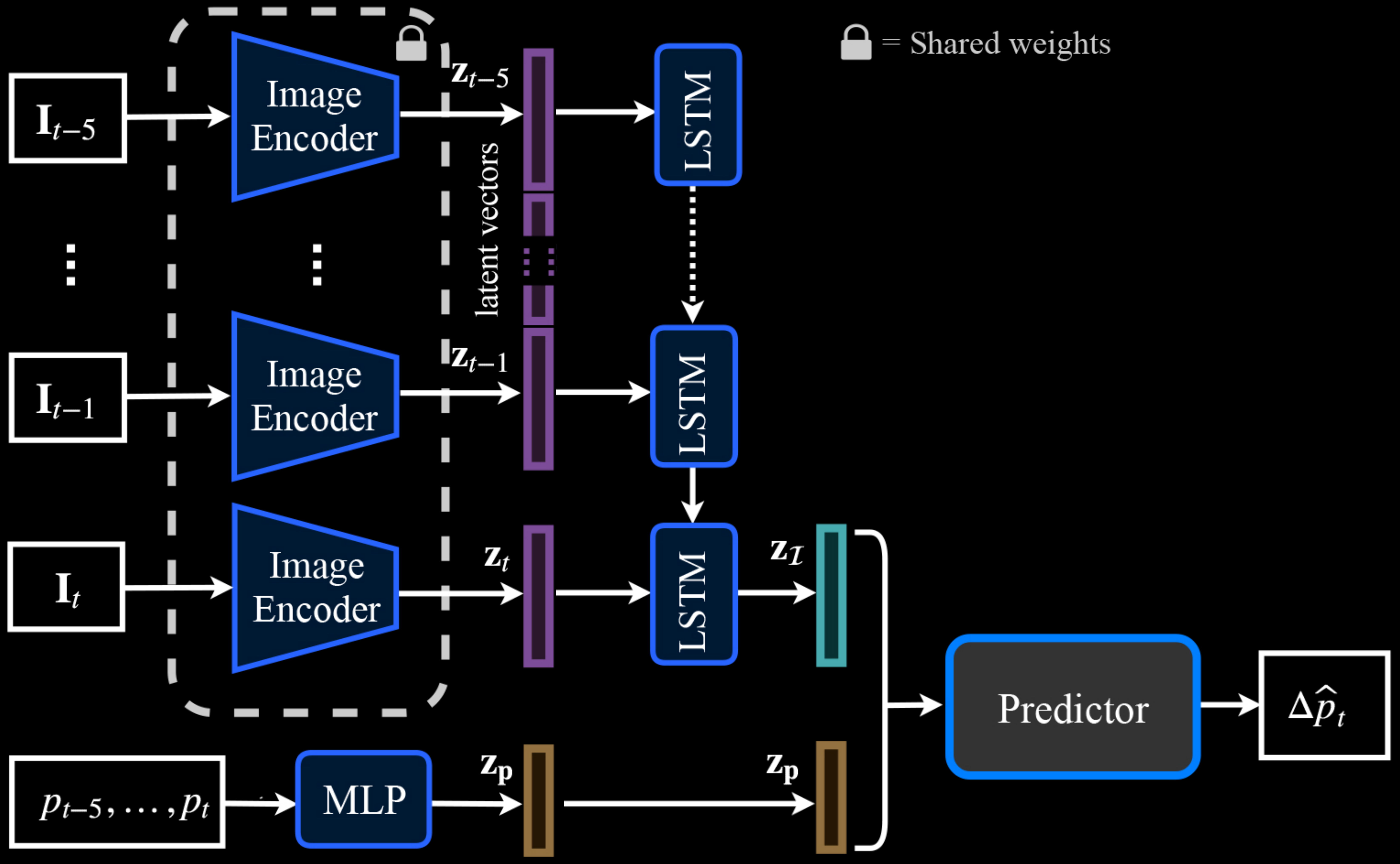
= Shared weights
$\mathbf{I}_{t-5}$
Image Encoder
$\mathbf{z}_{t-5}$
latent vectors
$\mathbf{I}_{t-1}$
Image Encoder
$\mathbf{z}_{t-1}$
$\mathbf{I}_t$
Image Encoder
$\mathbf{z}_t$
$p_{t-5}, \dots, p_t$
MLP
$\mathbf{z}_\mathbf{p}$

Power + image



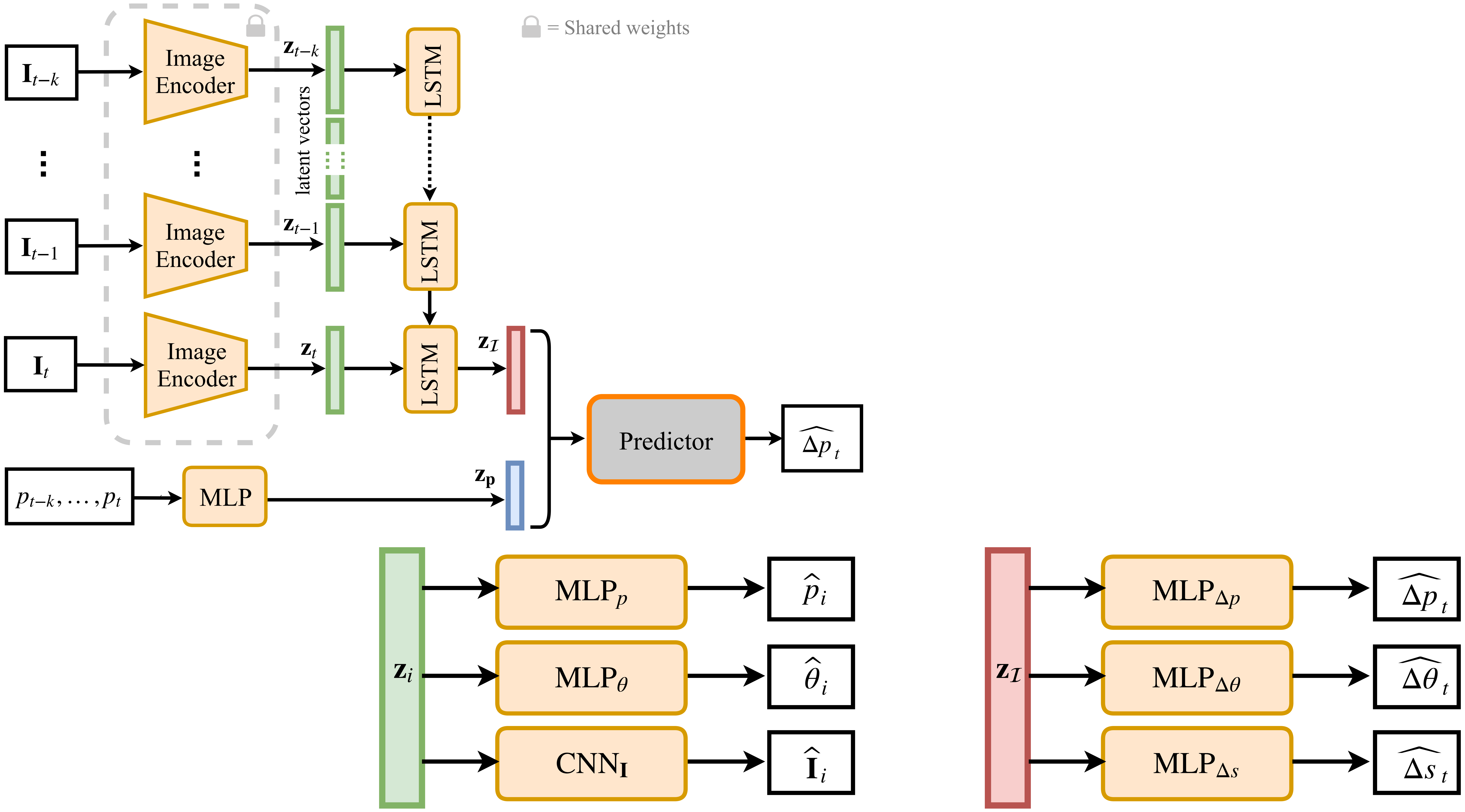
CNN

Power + image + temporal



LSTM

LSTM-FULL (PV + Image) with Multitask learning:



Outline

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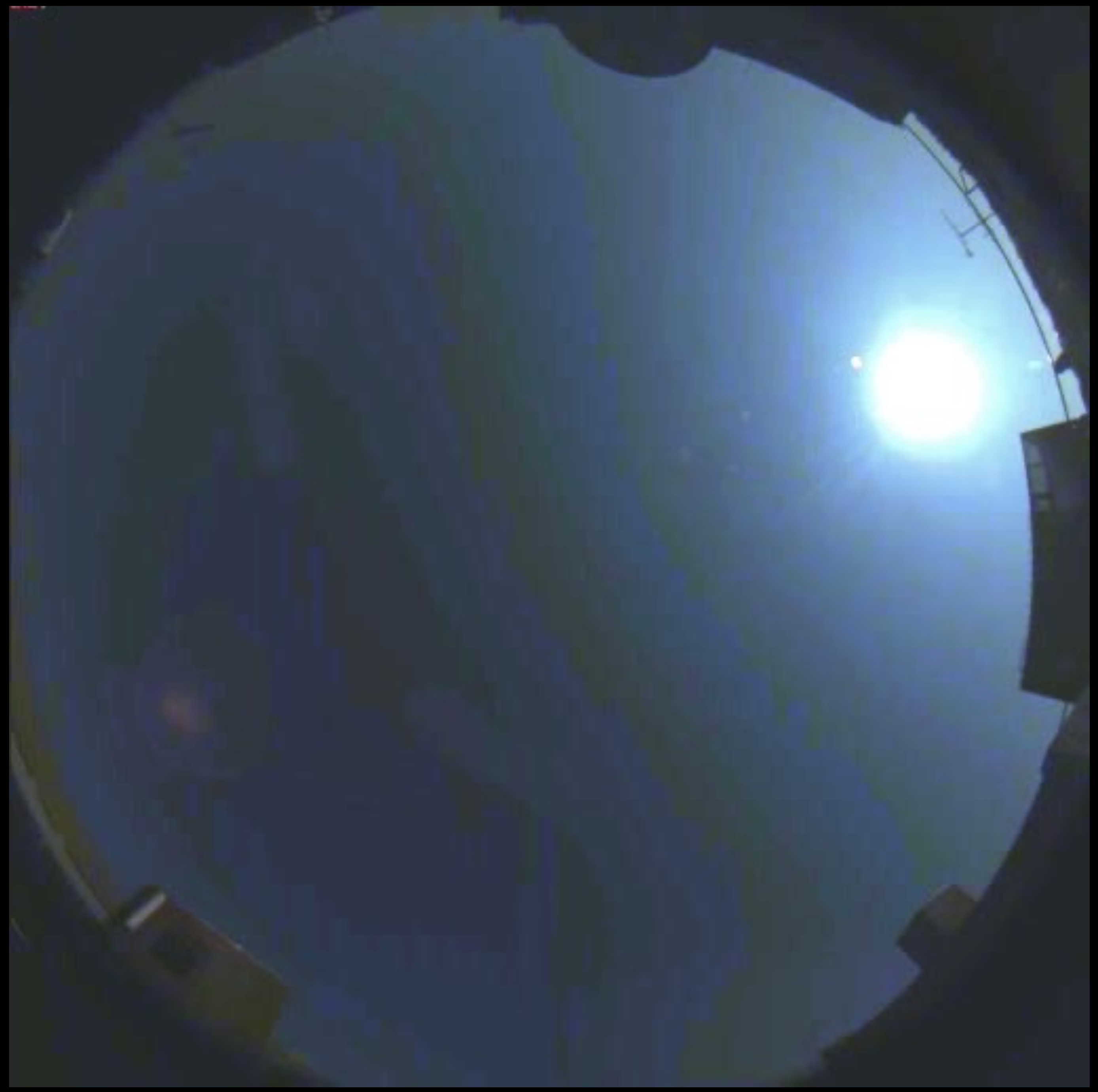
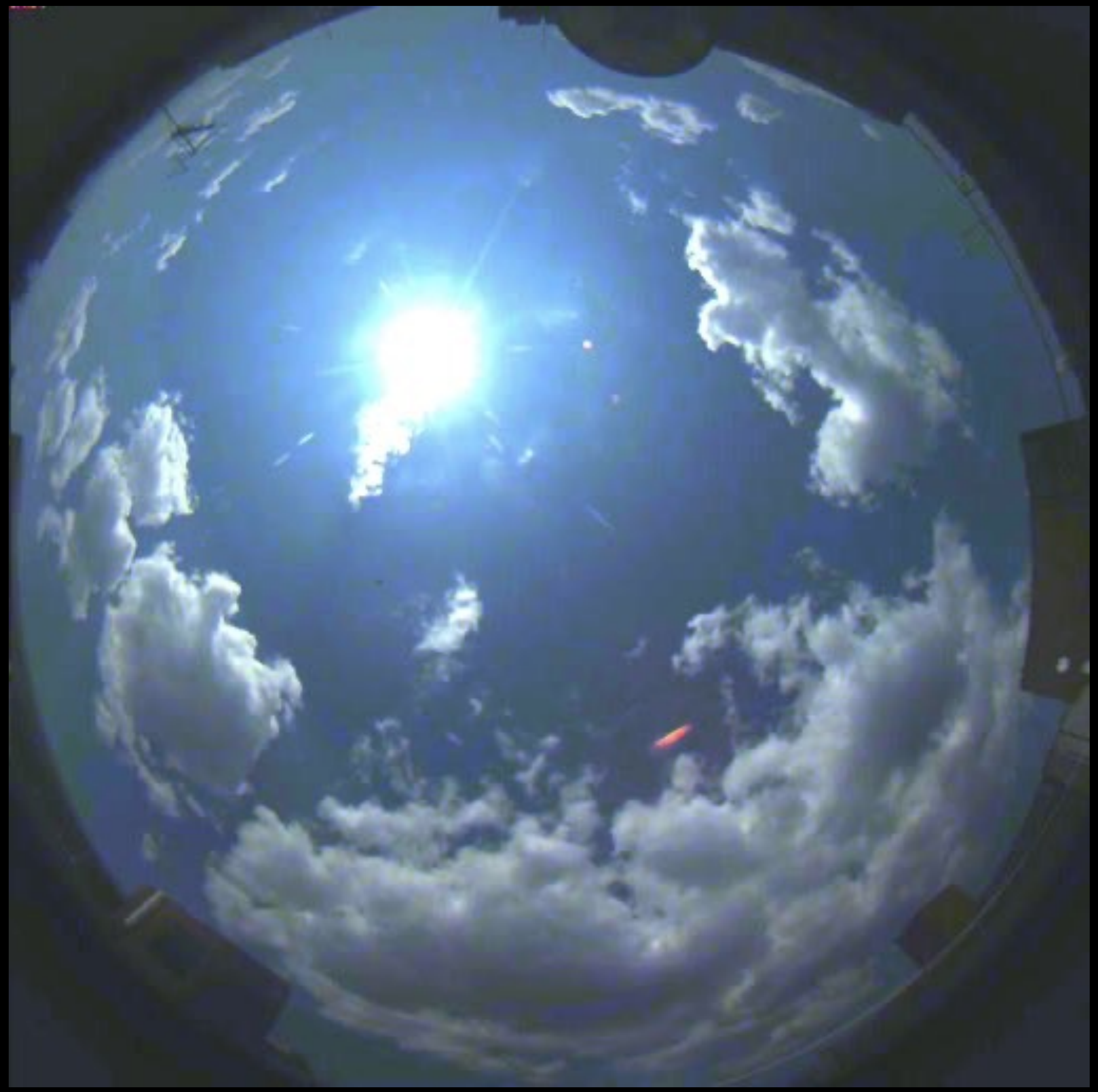
Evaluation

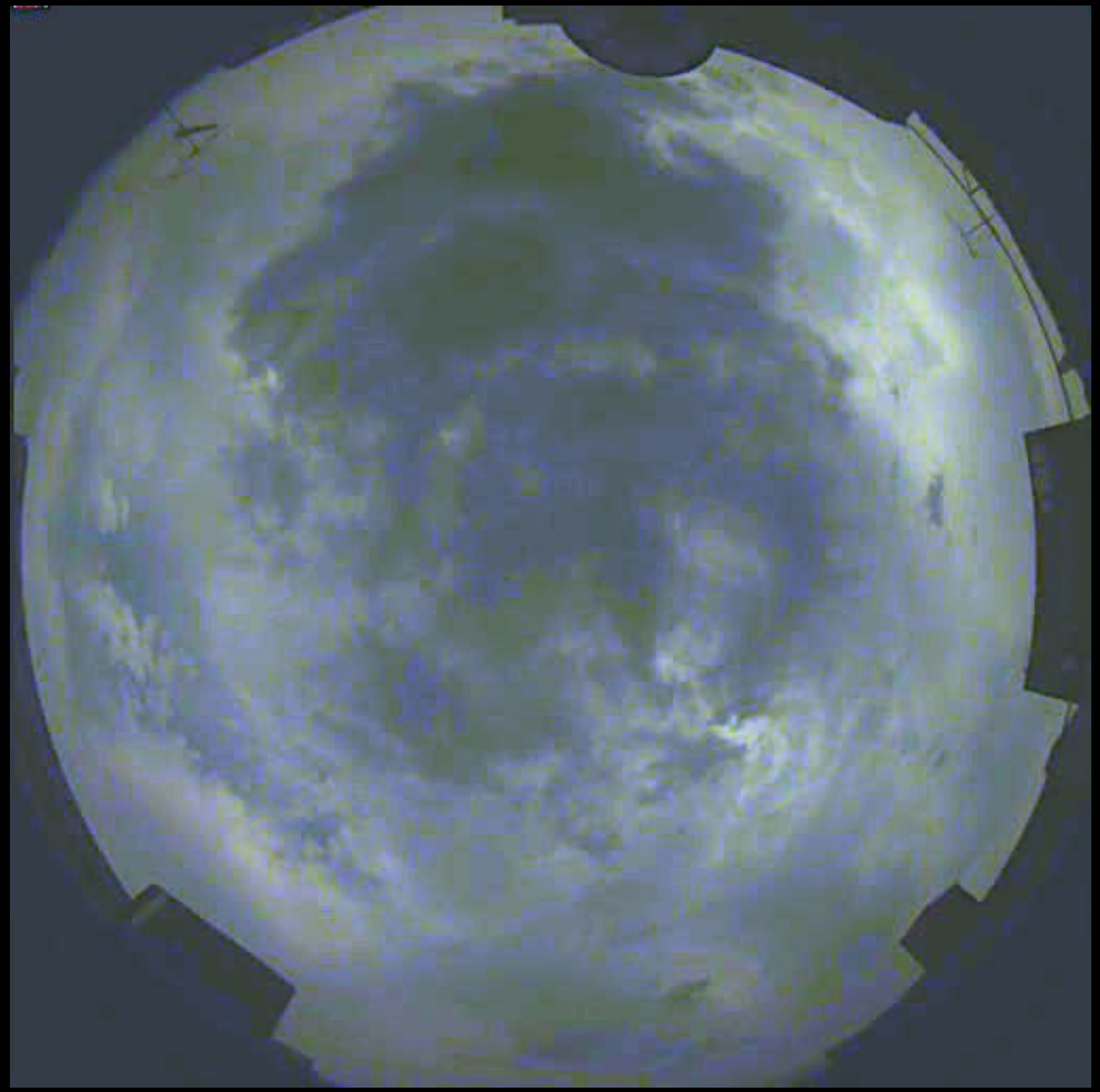
Different weather conditions for the test dataset



Clear: < 10% clouds



Partially cloudy: [10%, 90%] clouds



Overcast: >90% clouds

Persistence model: another baseline

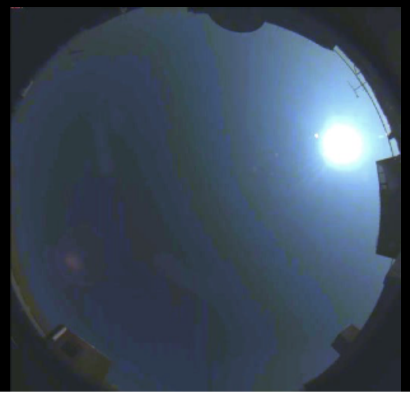
- assumes the future will be the same as the present

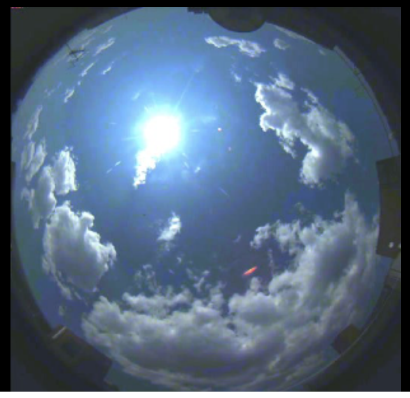
$$\Delta p_{t_0} = 0$$

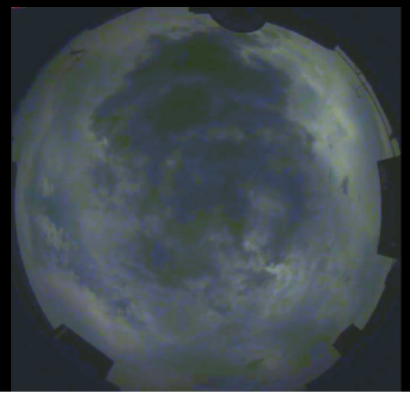
- known to be difficult to outperform for short lead times

1-min future MAE

Model







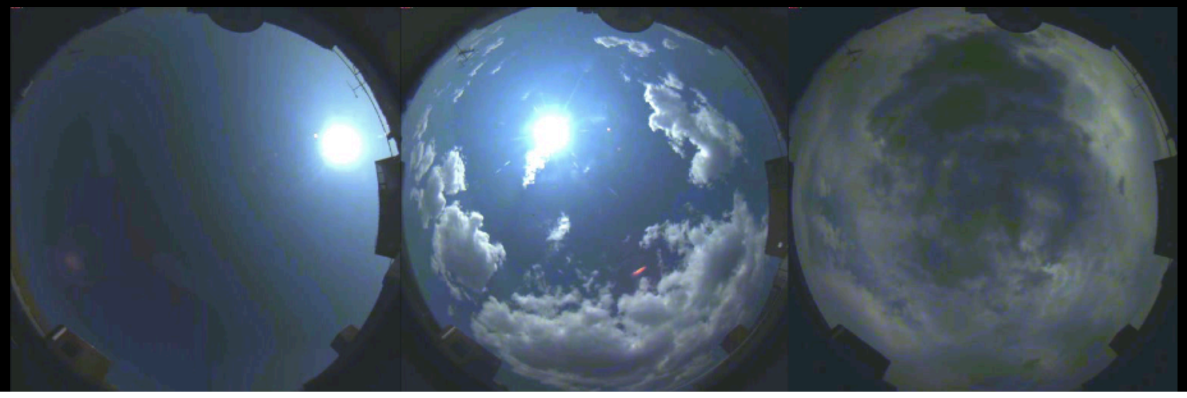


Table 2: Prediction for 1-min future. All metrics are reported in watts.

Model	clear		partially cloudy		overcast		all	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
Persistence	8.4	18.3	144.2	257.6	51.7	94.2	81.6	177.5
MLP	6.7	15.6	131.5	238.6	45.8	85.4	73.4	163.7
CNN	6.1	16.4	131.5	227.9	41.2	83.6	68.6	156.4
LSTM	**5.5**	15.5	**107.2**	**200.6**	40.8	82.8	61.1	**139.3**
LSTM-Full	5.6	**15.3**	109.2	203.1	**36.1**	**76.9**	**60.7**	140.5

All metrics are reported in watts.

Evaluation

Skill Score: compare different models.

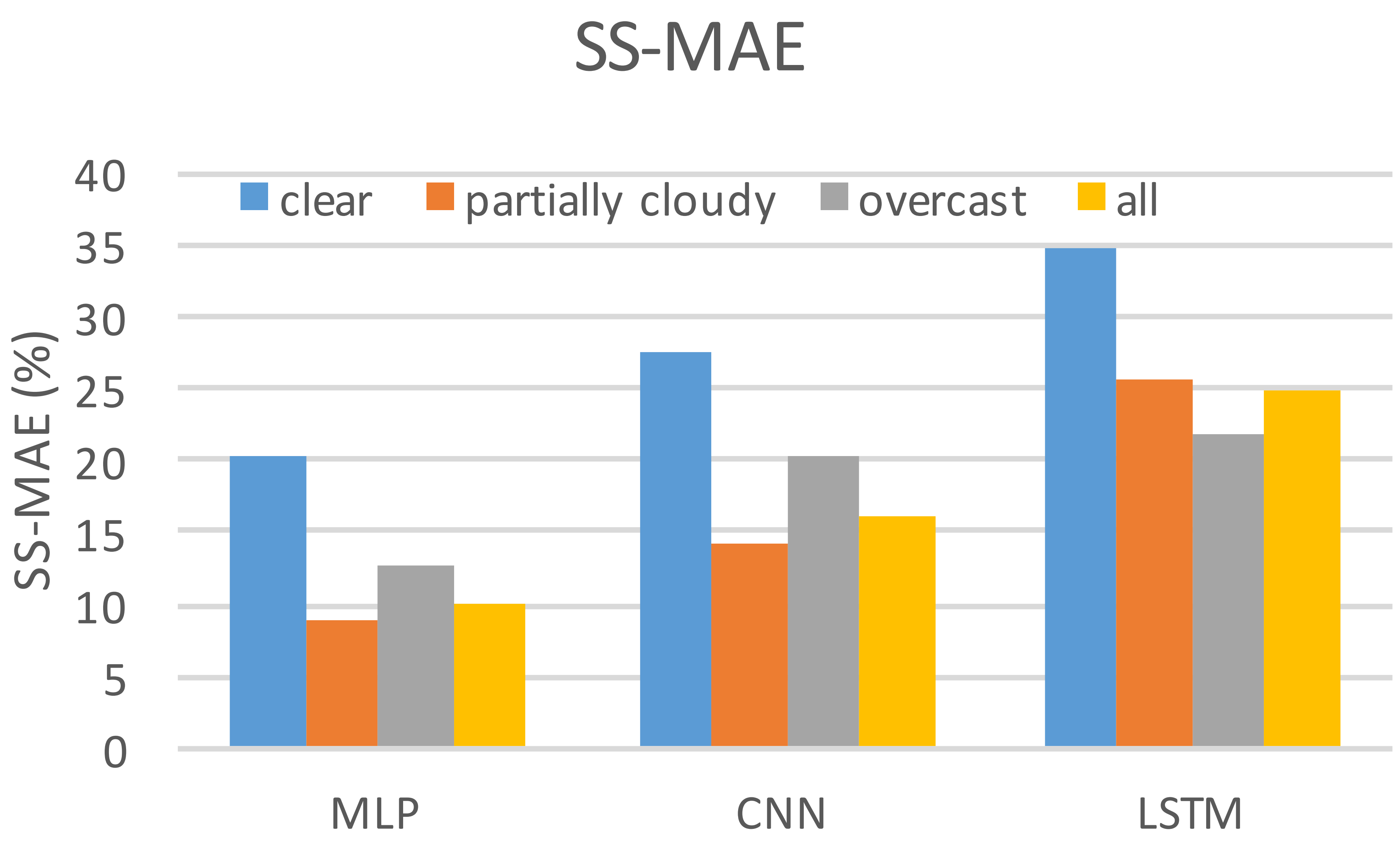
$$\mathrm{SS} = \left(1 - \frac{\mathcal{E}_{\mathrm{prediction}}}{\mathcal{E}_{\mathrm{baseline}}}\right) \times 100\%$$

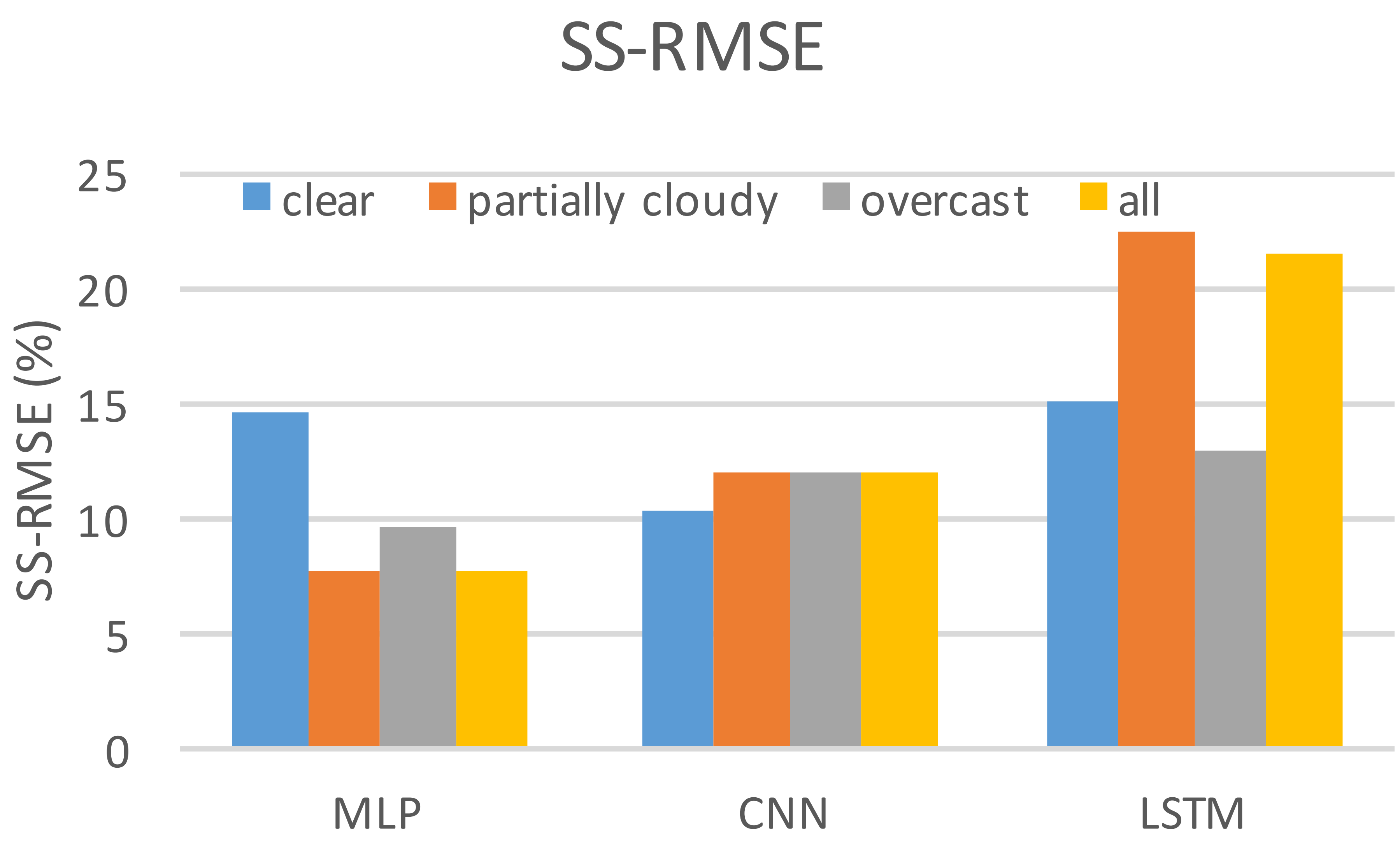
- > 0: prediction better than baseline
- $= 0$: prediction = baseline
- < 0: prediction worse than baseline

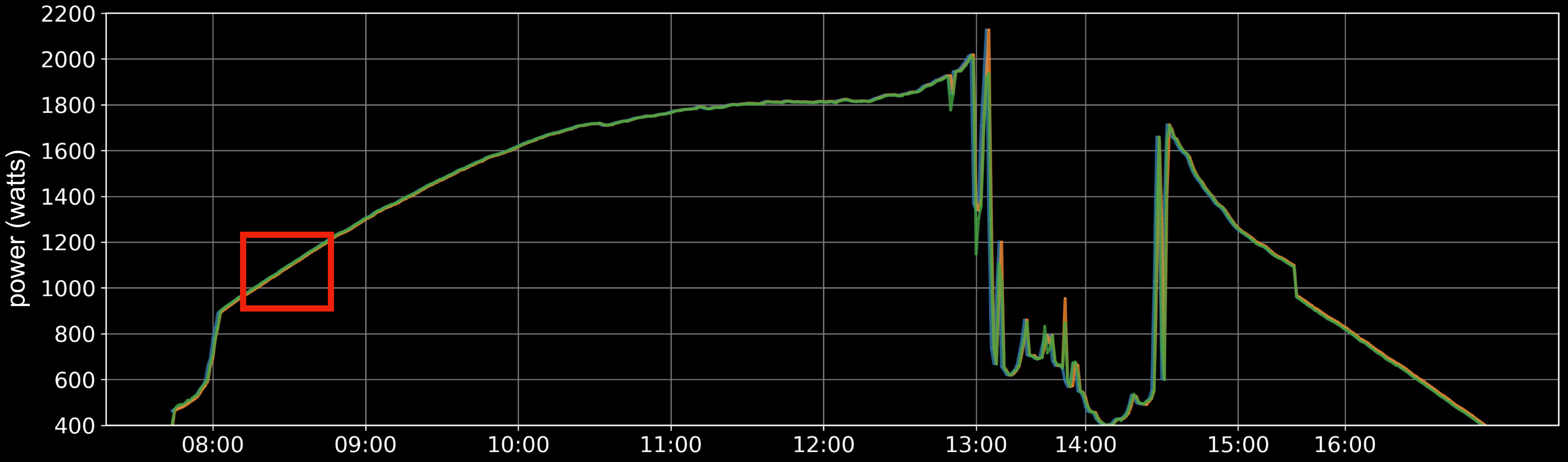
baseline = persistence

$\mathcal{E} \longrightarrow$ MAE & RMSE

Quantitative Evaluation






power (watts)
2200
2000
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1600
1400
1200
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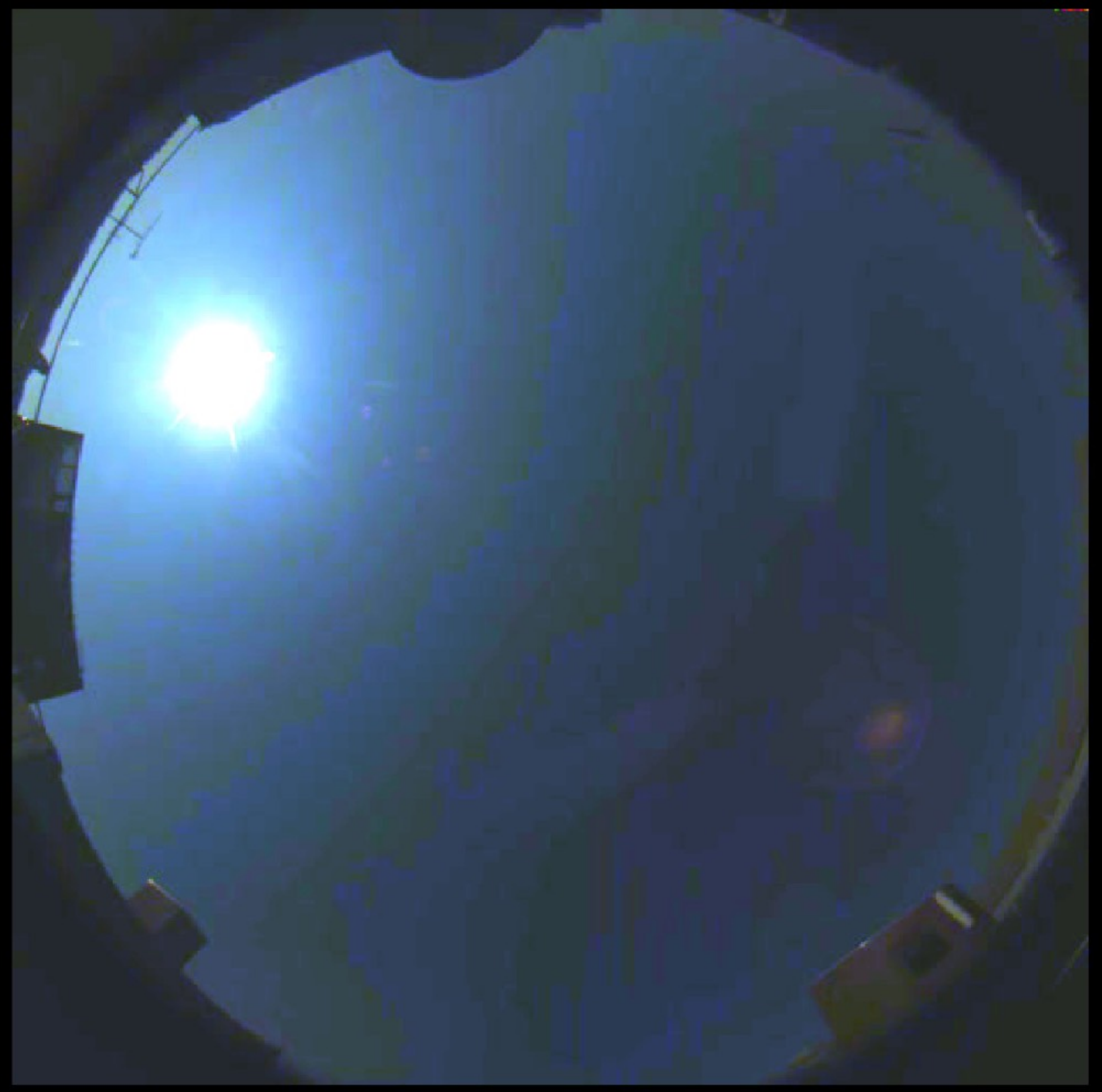
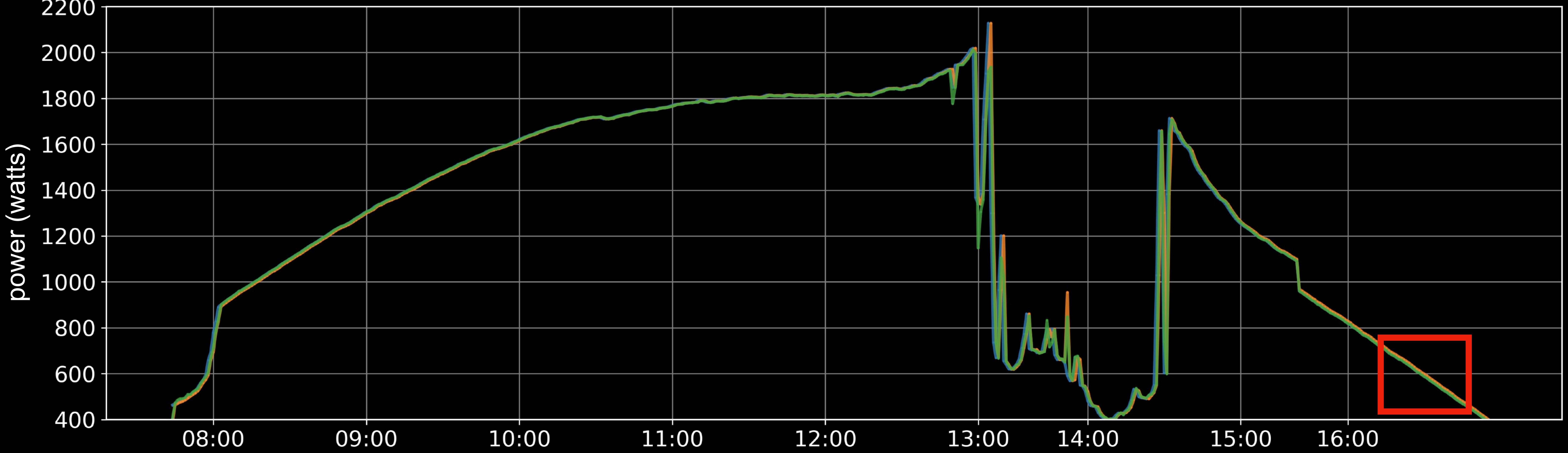
400
08:00
09:00
10:00
11:00
12:00
13:00
14:00
15:00
16:00


ground truth
prediction
persistence
1180
1160
1140
1120
1100
1080
1060
08:25
08:30
08:35
08:40




power (watts)
2200
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12:00
13:00
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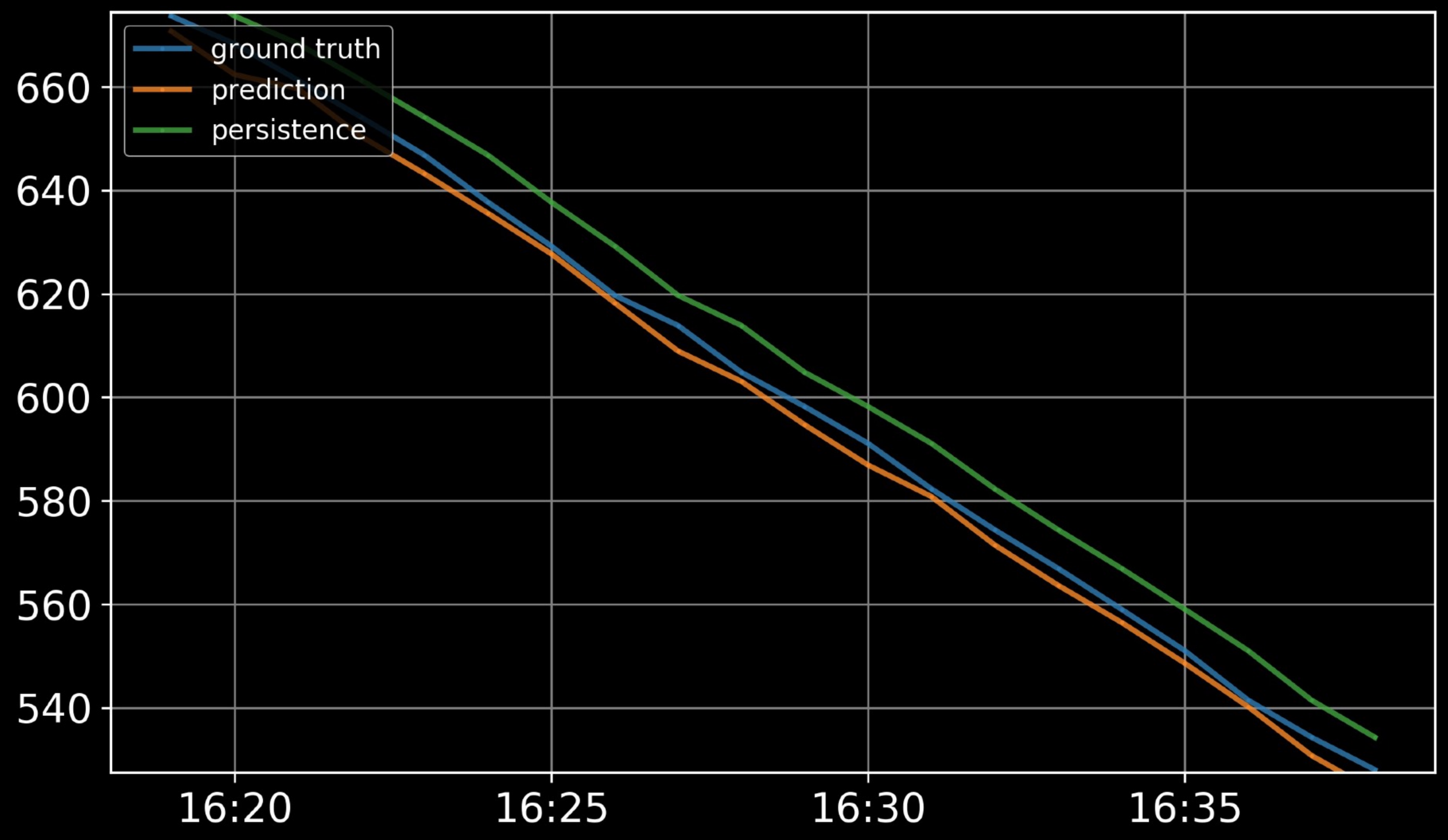
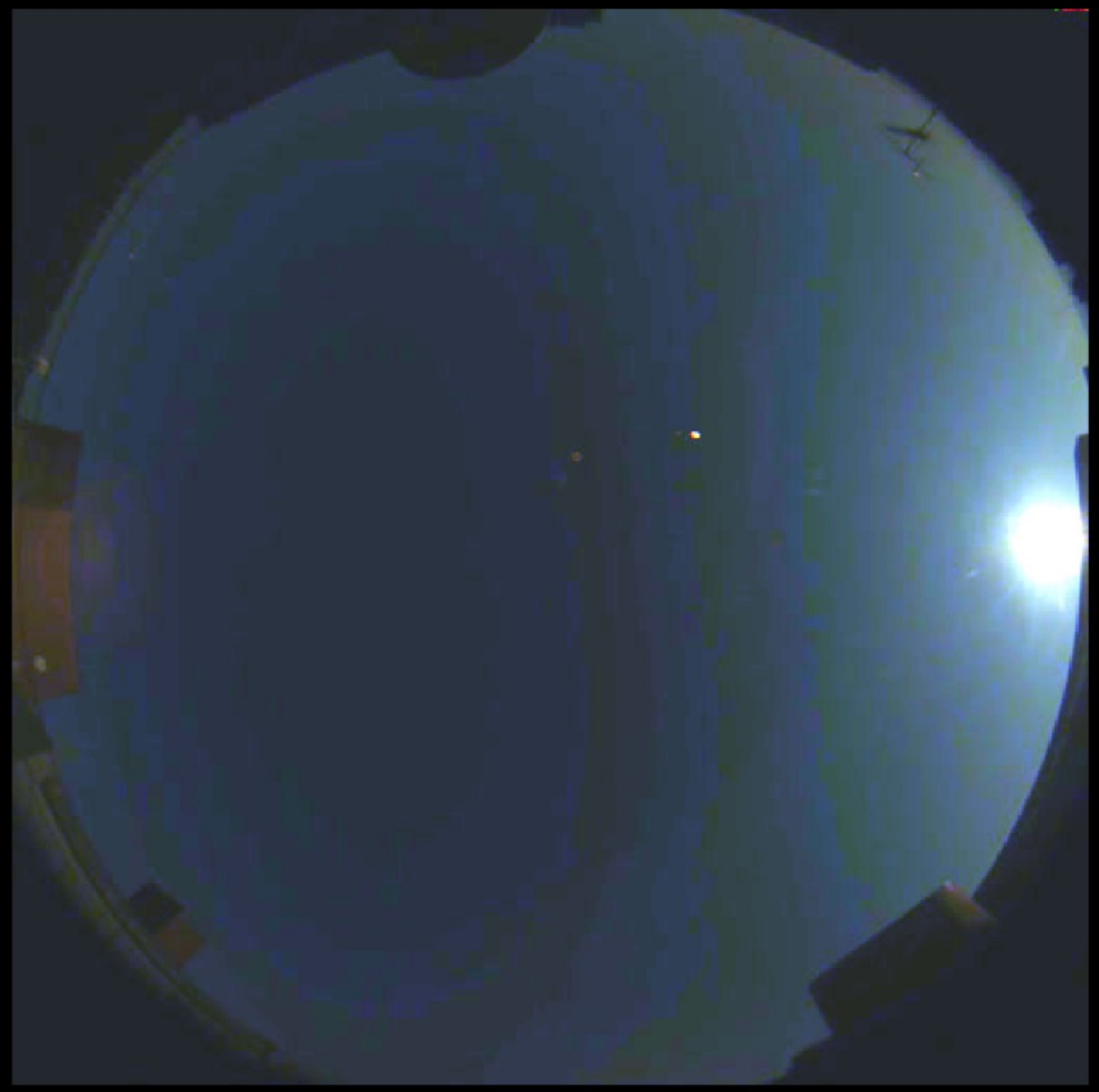
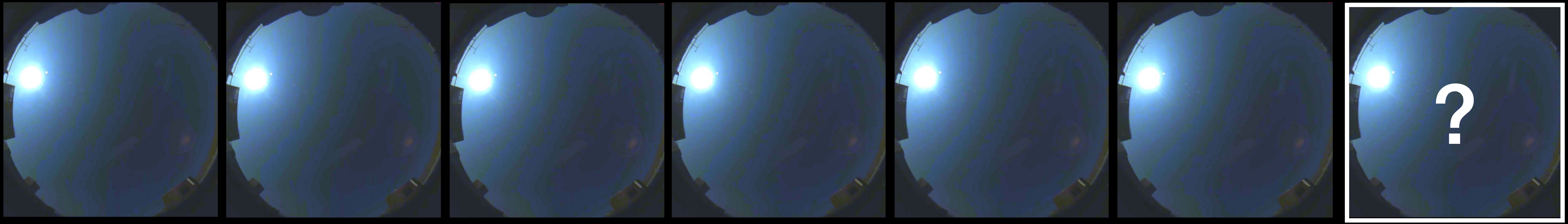

ground truth
prediction
persistence
660
640
620
600
580
560
540
16:20
16:25
16:30
16:35



Quiz

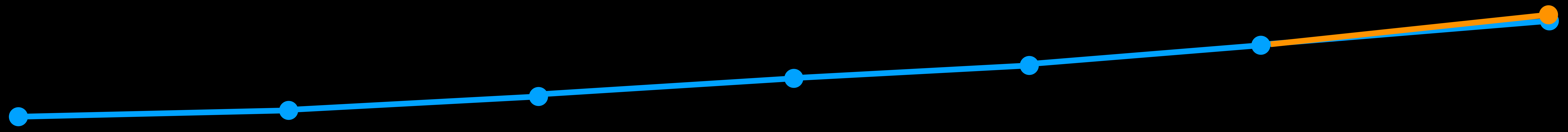
p_{t-5} p_{t-4} p_{t-3} p_{t-2} p_{t-1} p_t p_{t+1}



956.8 963.5 969.8 976.7 983.7 990.6 ?

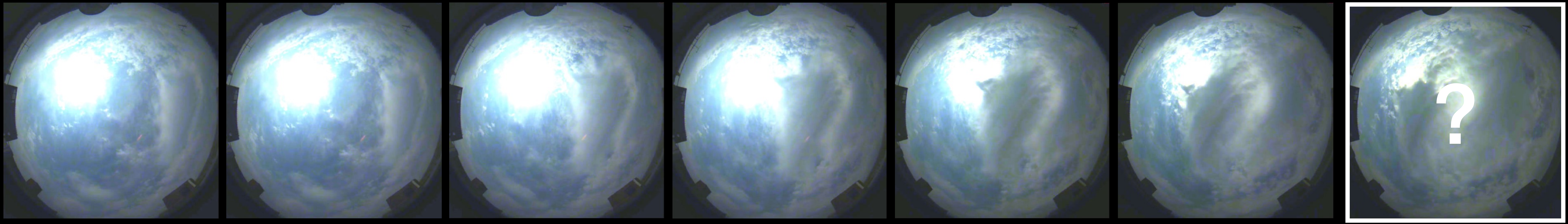
Prediction: 998.9

Ground truth: 998.5

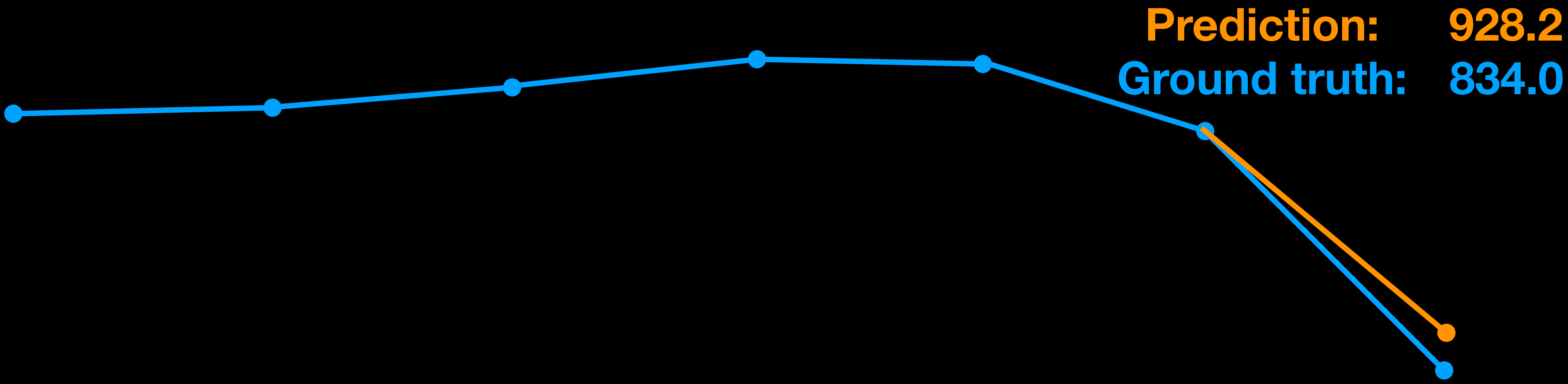


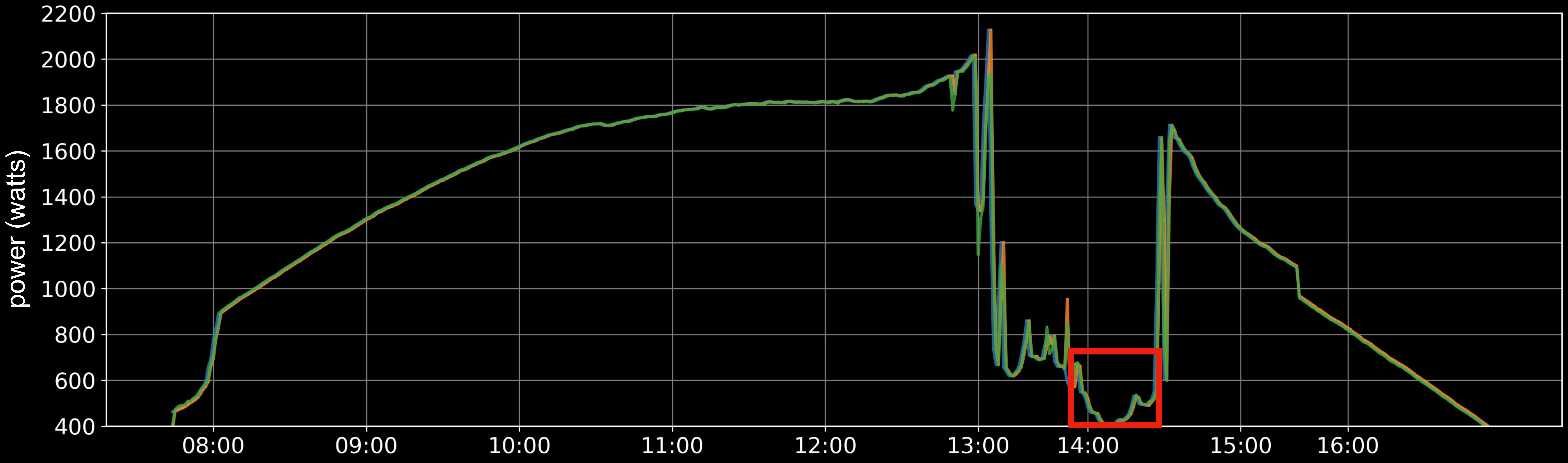
Quiz

p_{t-5}	p_{t-4}	p_{t-3}	p_{t-2}	p_{t-1}	p_t	p_{t+1}

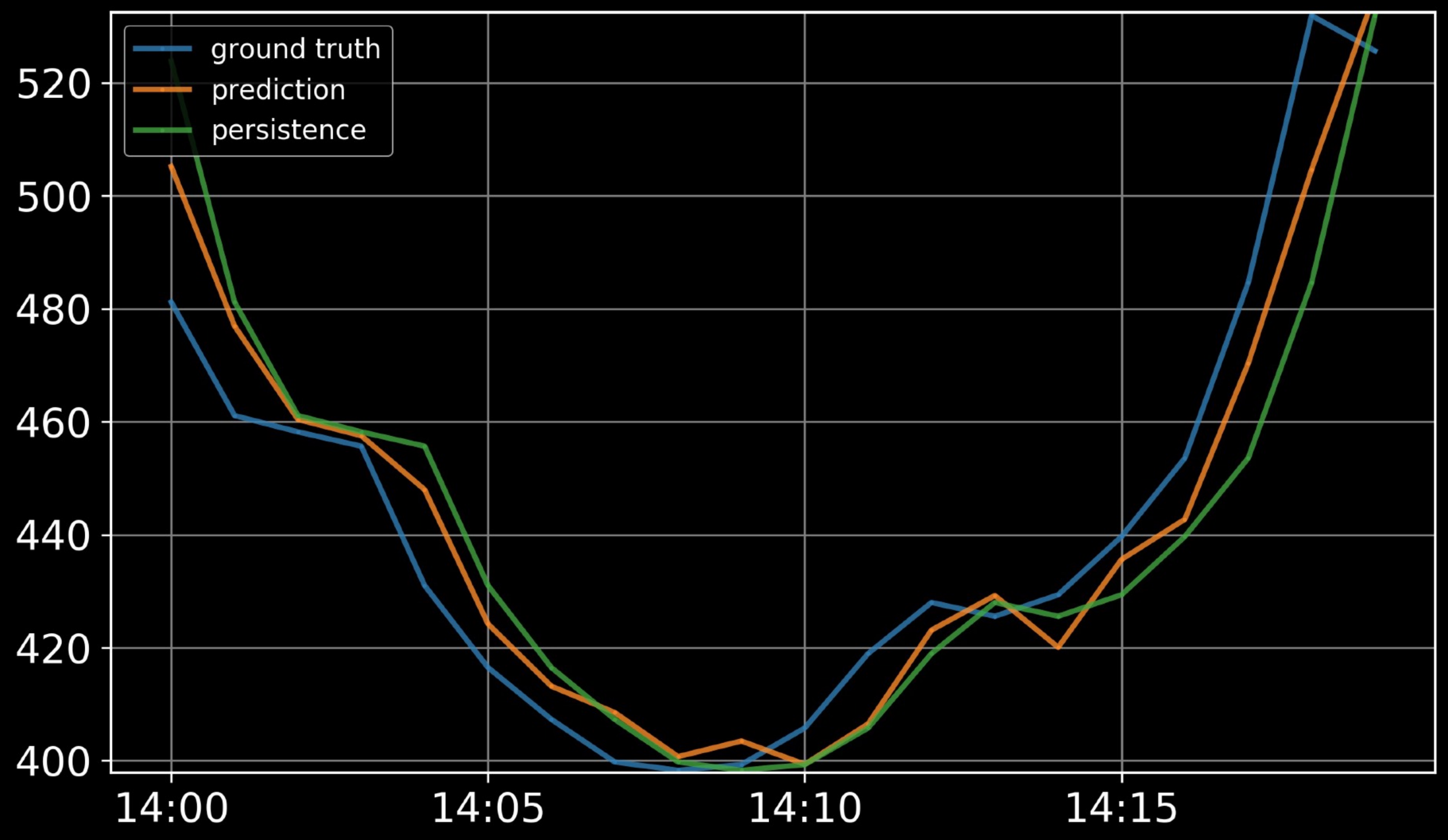


1516.5	1572.4	1687.7	1762.4	1709.9	1461.7	?

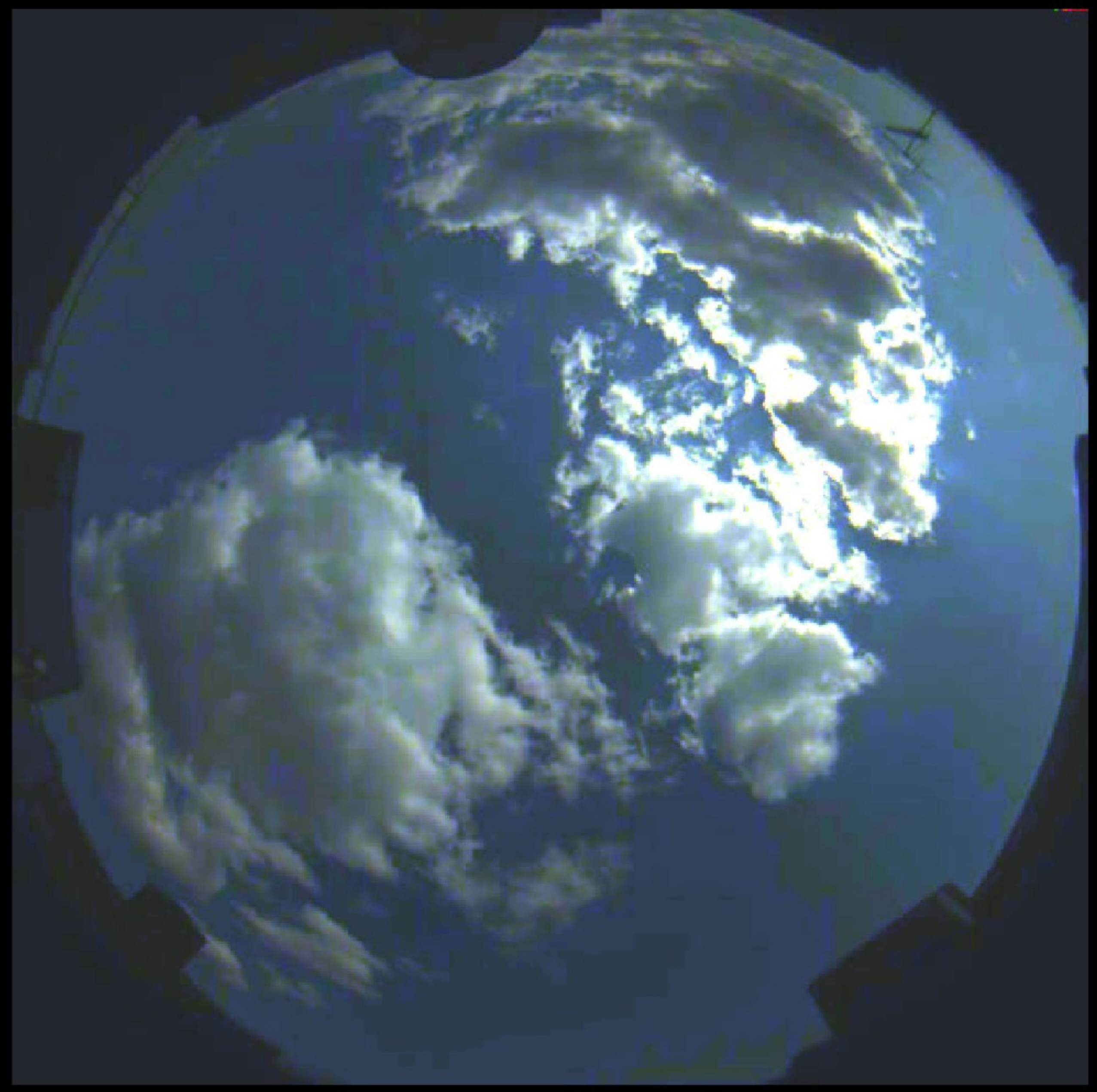


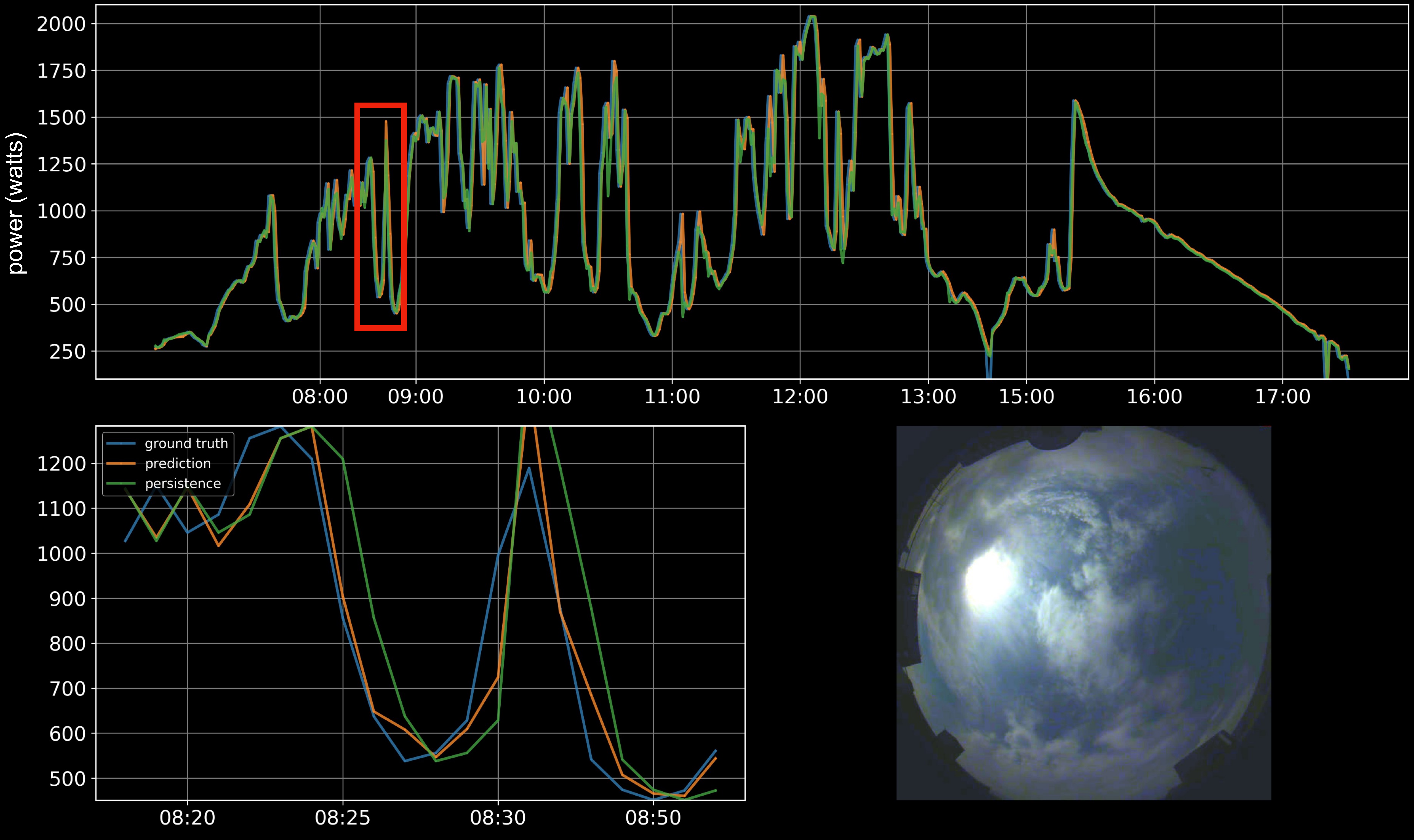


power (watts)
2200
2000
1800
1600
1400
1200
1000
800
600
400
08:00
09:00
10:00
11:00
12:00
13:00
14:00
15:00
16:00

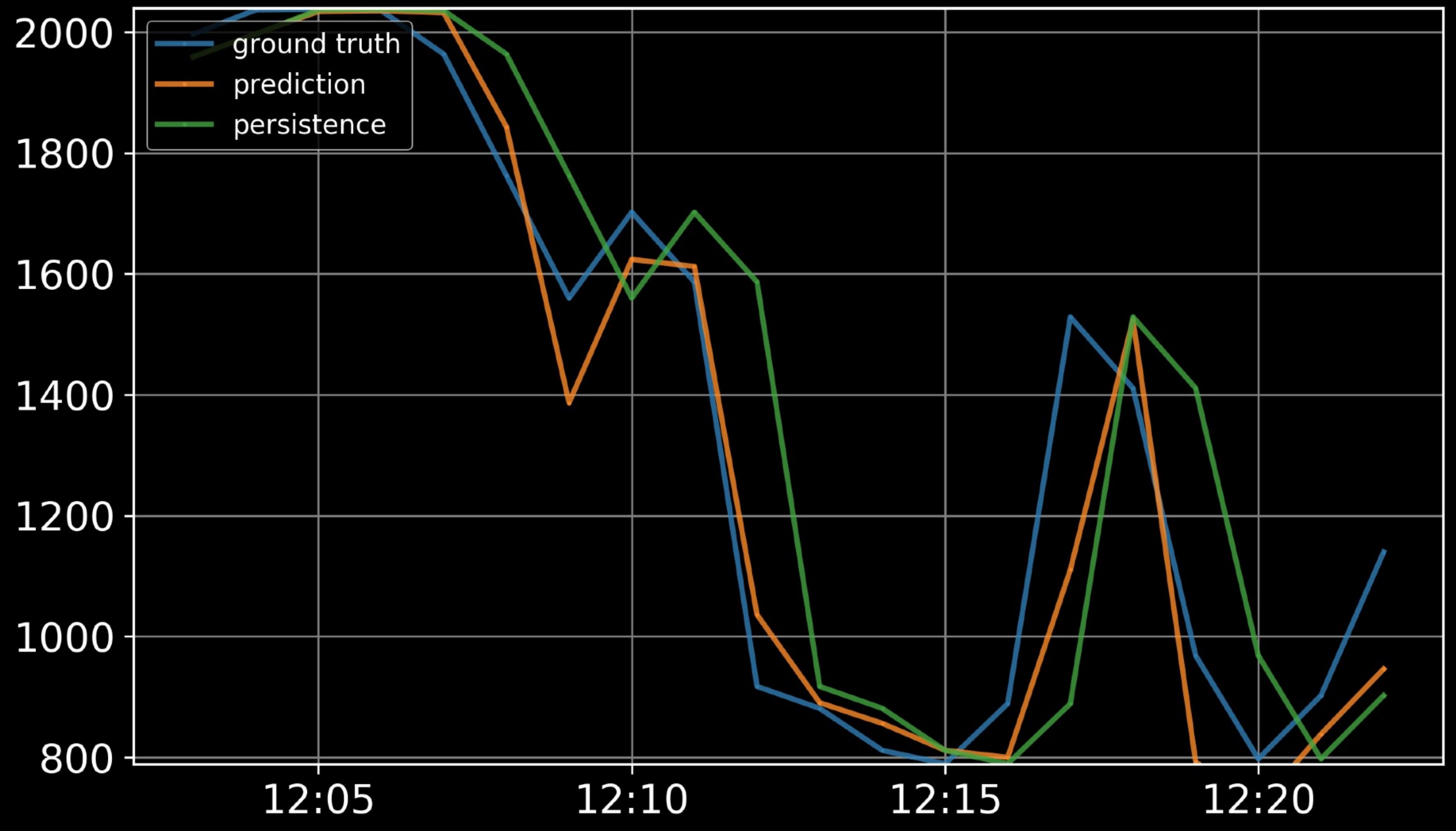


ground truth
prediction
persistence
520
500
480
460
440
420
400
14:00
14:05
14:10
14:15

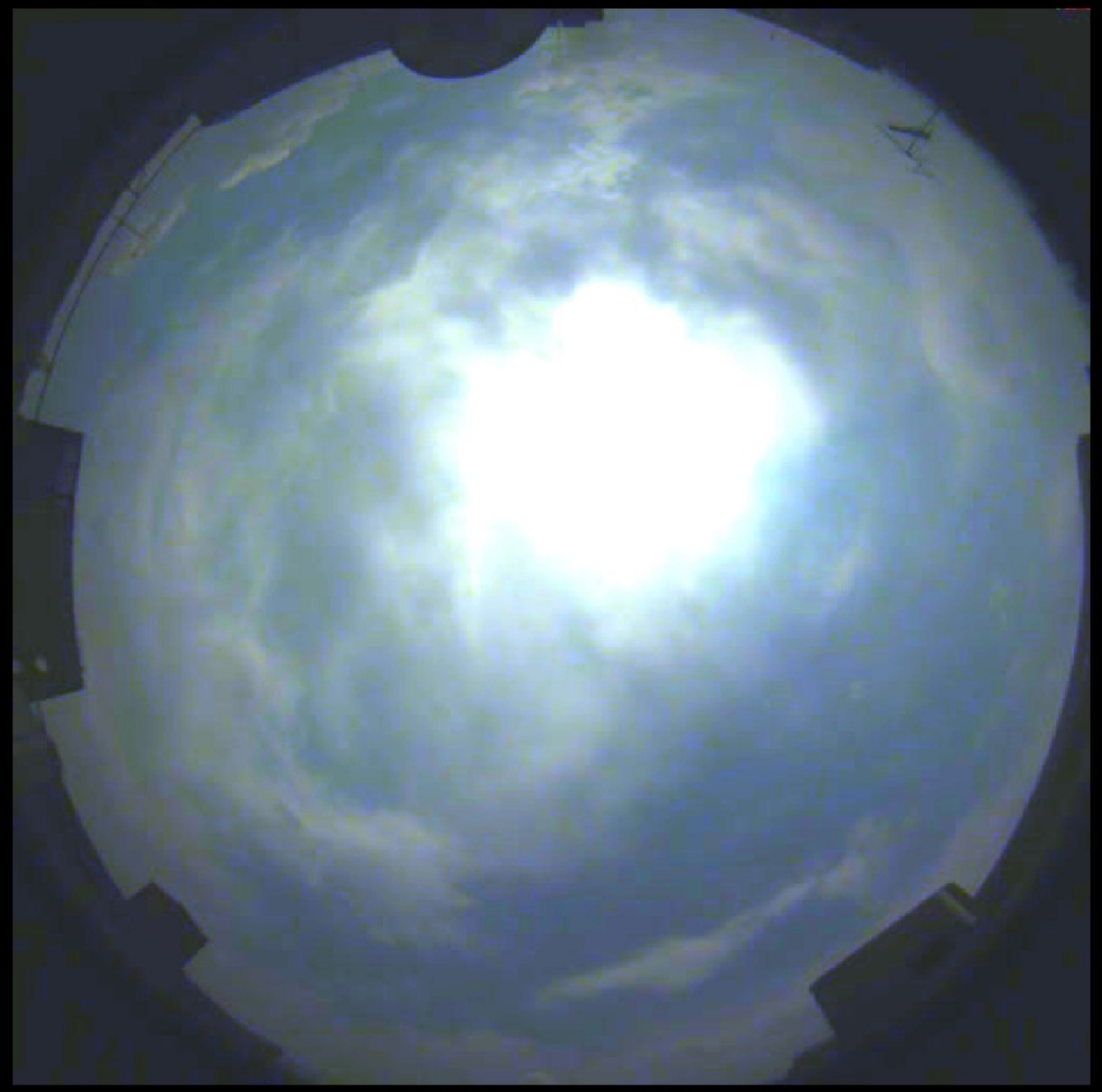


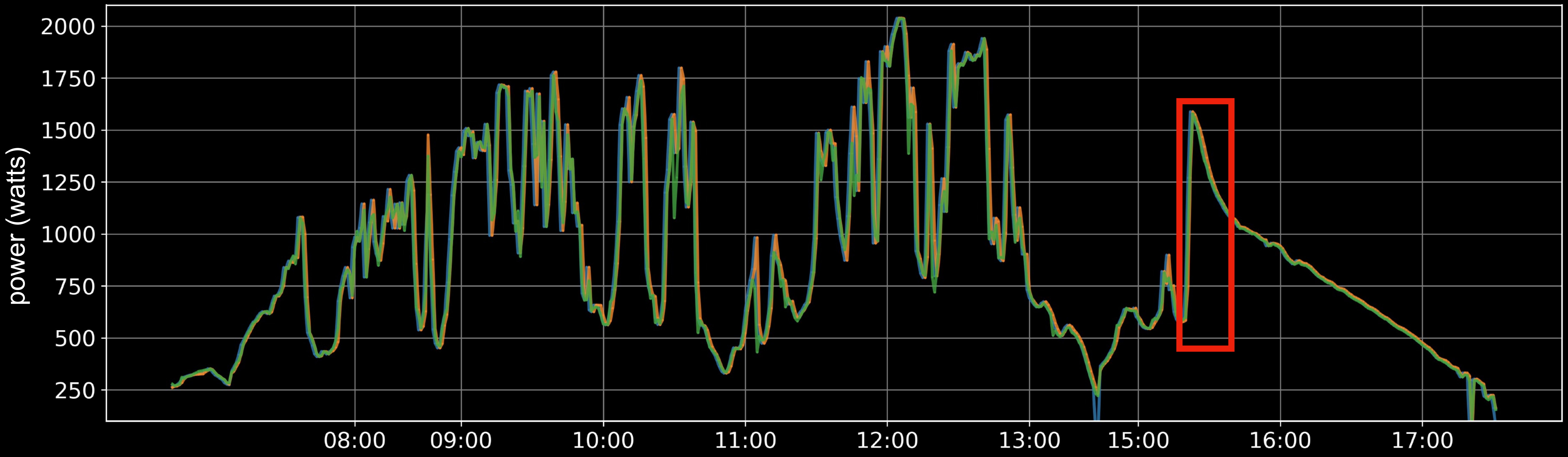

power (watts)
2000
1750
1500
1250
1000
750
500
250
08:00
09:00
10:00
11:00
12:00
13:00
15:00
16:00
17:00
ground truth
prediction
persistence
1200
1100
1000
900
800
700
600
500
08:20
08:25
08:30
08:50

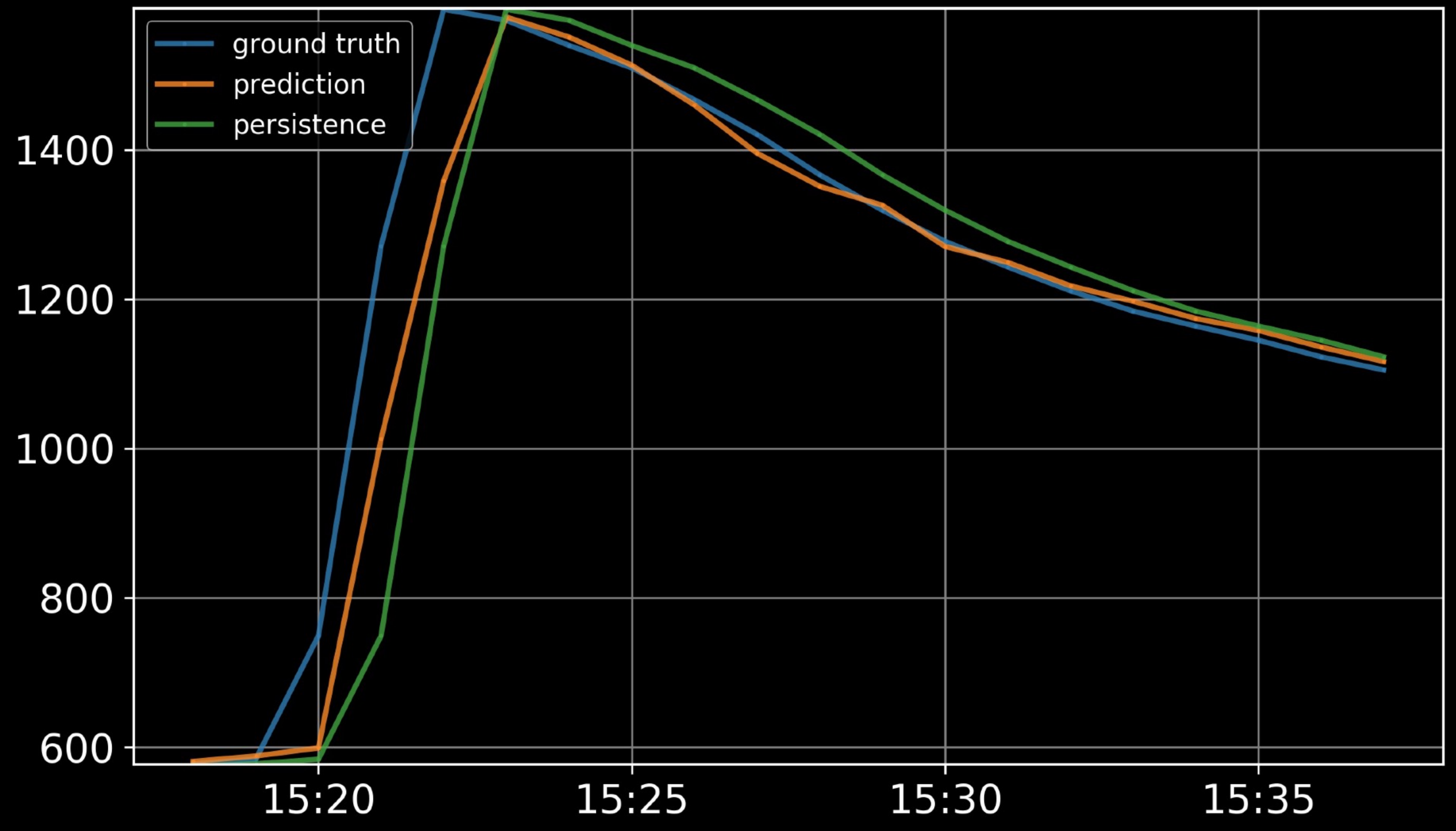
power (watts)
2000
1750
1500
1250
1000
750
500
250
08:00
09:00
10:00
11:00
12:00
13:00
15:00
16:00
17:00

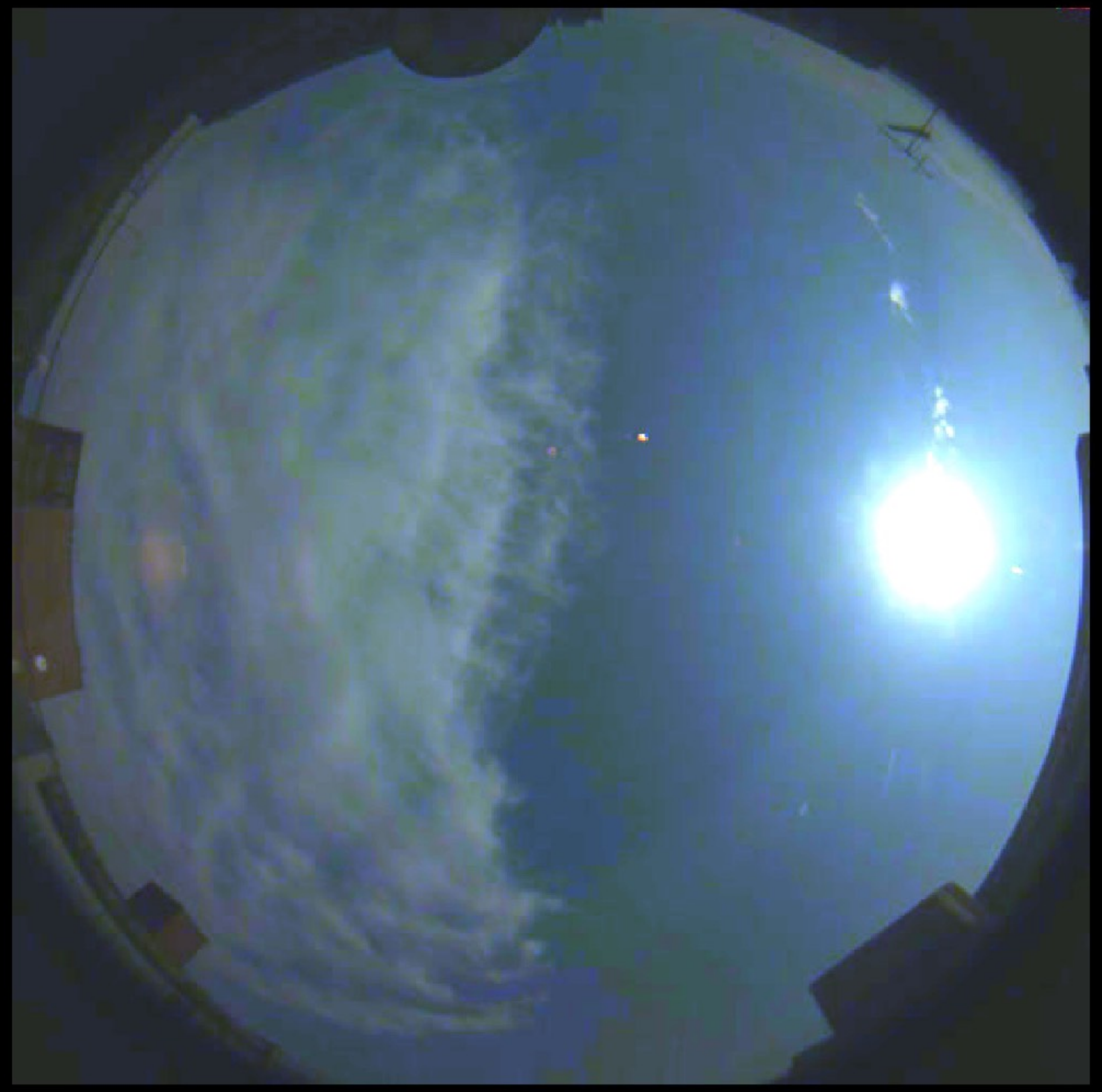


ground truth
prediction
persistence
2000
1800
1600
1400
1200
1000
800
12:05
12:10
12:15
12:20




power (watts)
2000
1750
1500
1250
1000
750
500
250
08:00
09:00
10:00
11:00
12:00
13:00
15:00
16:00
17:00


ground truth
prediction
persistence
1400
1200
1000
800
600
15:20
15:25
15:30
15:35



Conclusion

Directly learn a mapping between past PV, past images and future PV.

1. **Apply deep learning to the photovoltaic nowcasting problem**
2. **Present different architectures to predict the 1-minute future**
3. **Vastly outperforming the baseline model**