Deep Photovoltaic Nowcasting

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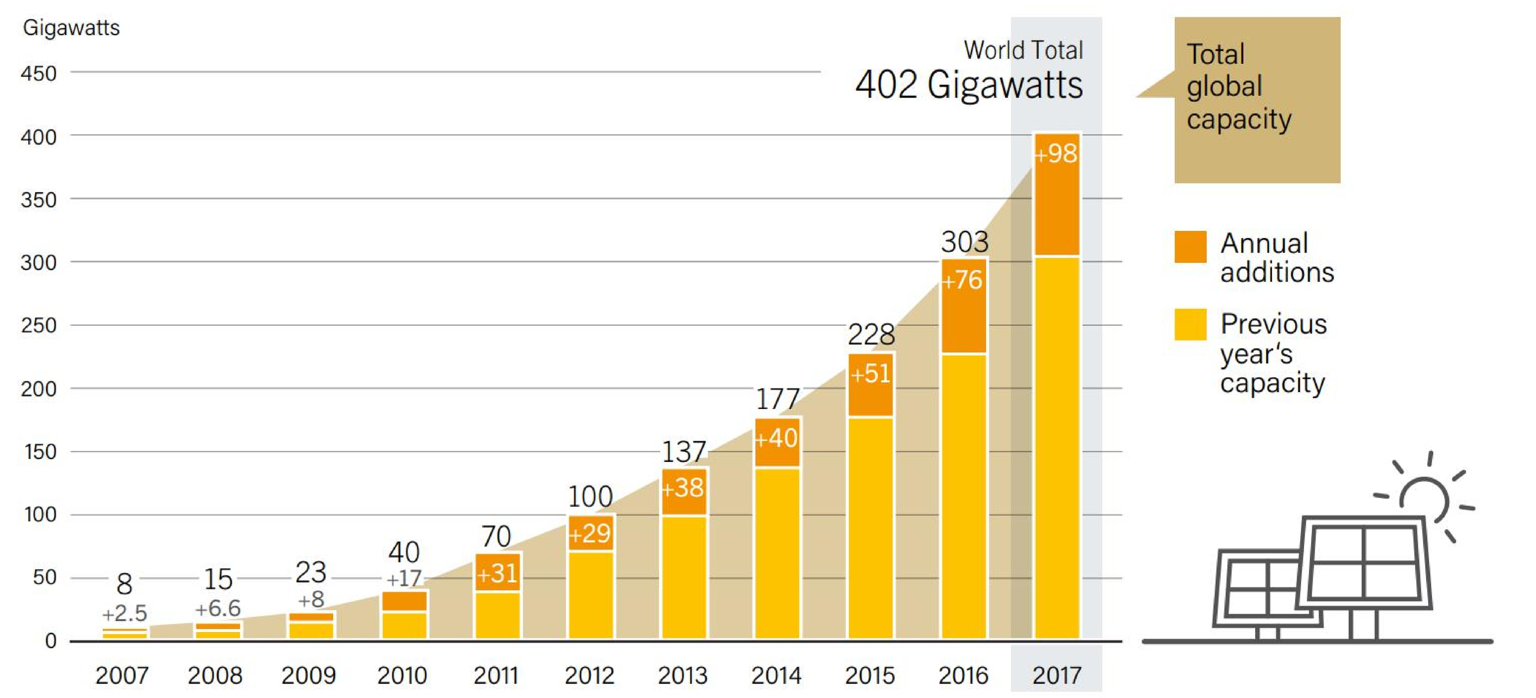
Motivation

As opposed to traditional means of energy production, solar energy depends on the varying illumination conditions.

- Short term photovoltaic (PV) forecasting is critical to the operation of the smart grid
- Solar energy global capacity, 2007-2017



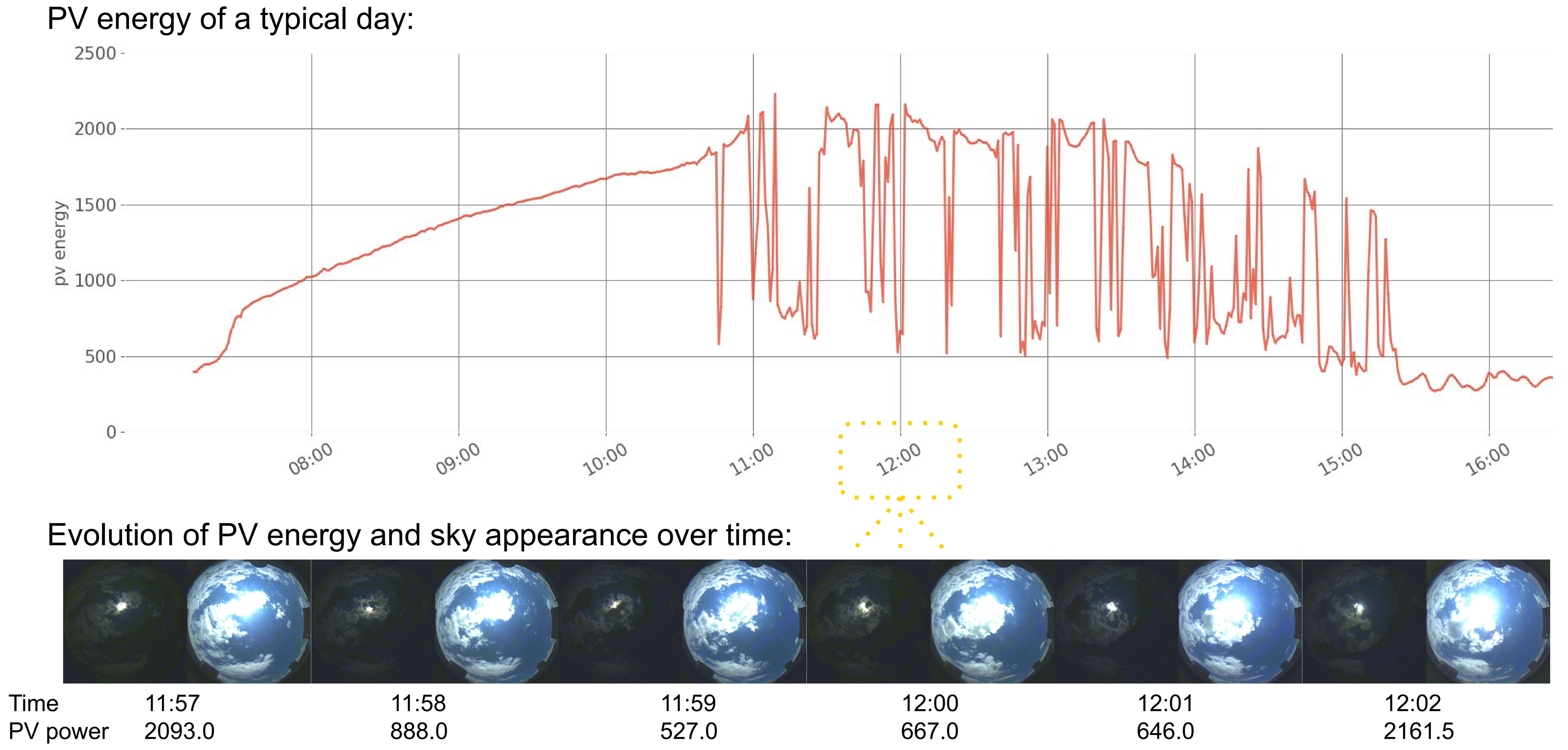
RENEWABLES 2018 GLOBAL STATUS REPORT

Challenge

- Solar power at ground level is intermittent which highly depends on cloud cover.
- Short term cloud changes such as velocity, direction, formation and destruction are very difficult to predict.

PV energy of a typical day:

Evolution of PV energy and sky appearance over time:



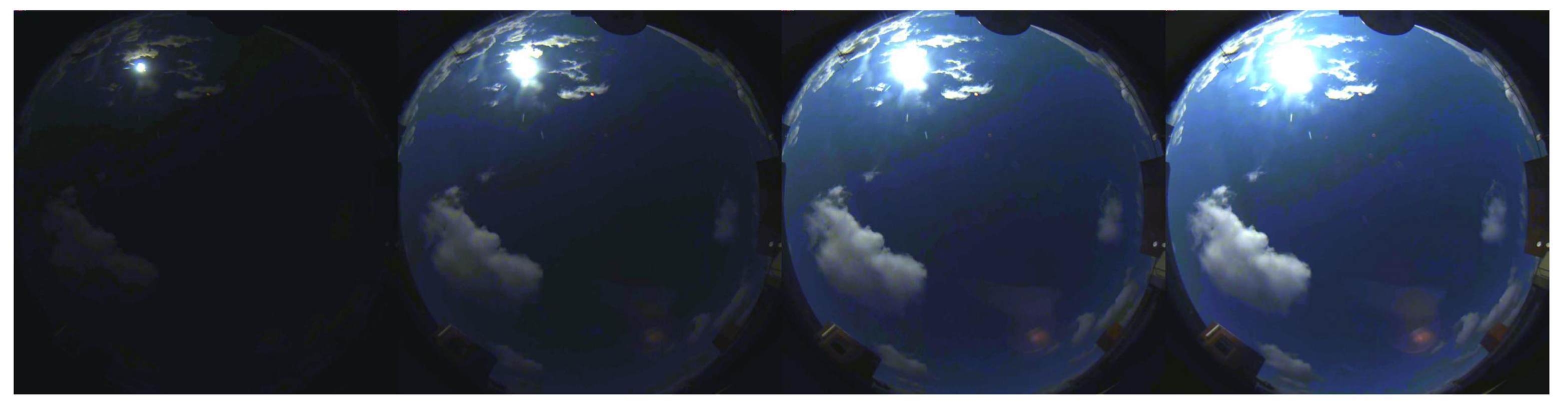
Data

90 days in total: captured sky image along with its PV energy

- PV energy is recorded at PV cells
- 4 images are captured with different exposures
  - Sky camera is mounted close to the PV panel equipped with a fisheye lens pointing to zenith

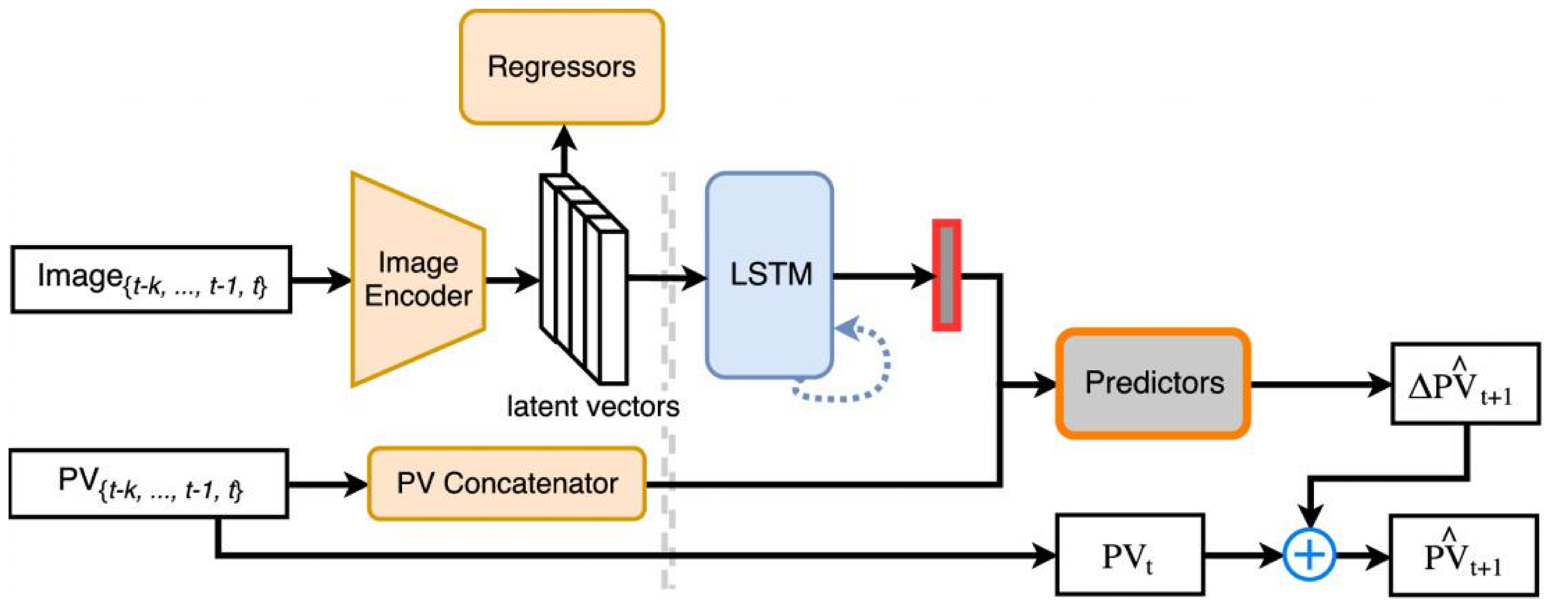
Data are splitted according to days

- 80%(72 days) for training
- 20%(18 days) for test



11ms 88ms 176mm 264mm

Network Architecture



- Image Encoder: compressing input image into a latent vector
- Regressors: regressing pv $\mathbf{y}_{pv}$, sun position $\mathbf{y}_\theta$, and input image $\mathbf{y}_I$
- Predictors: predicting the change of pv $\Delta\mathbf{y}_{pv}$, sun position $\Delta\mathbf{y}_\theta$ and sun intensity $\Delta\mathbf{y}_{sun}$
- PV Concatenator: taking the historical pv into the network

$$\mathcal{L}^r_{pv} = ||\mathbf{y}_{pv} - \mathbf{t}_{pv}||_2$$
$$\mathcal{L}^r_\theta = ||\mathbf{y}_\theta - \mathbf{t}_\theta||_2$$
$$\mathcal{L}^r_I = ||\mathbf{y}_I - \mathbf{t}_I||_2$$
$$\mathcal{L}^p_{pv} = ||\Delta\mathbf{y}_{pv} - \Delta\mathbf{t}_{pv}||_2$$
$$\mathcal{L}^p_\theta = ||\Delta\mathbf{y}_\theta - \Delta\mathbf{t}_\theta||_2$$
$$\mathcal{L}^p_{sun} = ||\Delta\mathbf{y}_{sun} - \Delta\mathbf{t}_{sun}||_2$$

Results

Performance on the test dataset

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

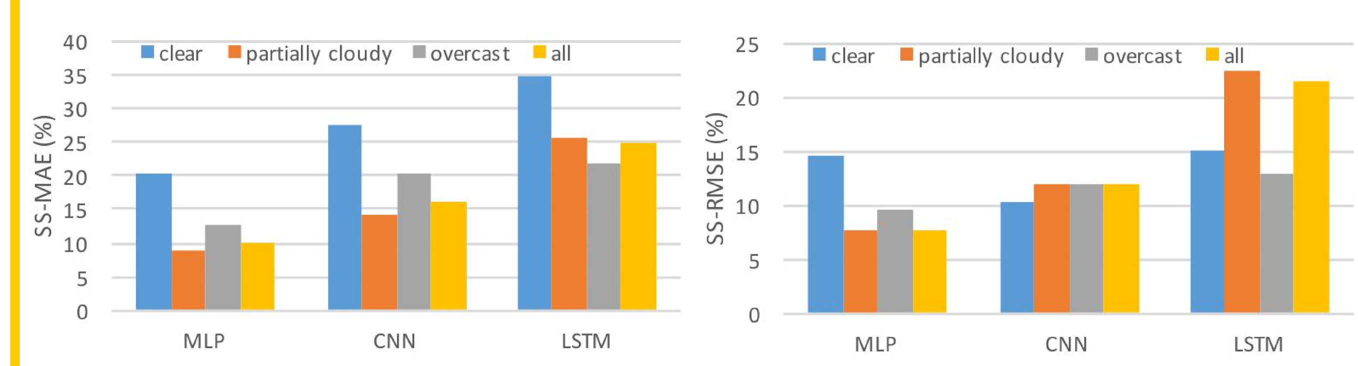
Model	clear		partially cloudy		overcast		all	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
Persistence	8.4	18.3	144.2	257.6	51.7	94.2	81.6	177.5
MLP	6.7	15.6	131.5	238.6	45.8	85.4	73.4	163.7
CNN	6.1	16.4	123.5	227.9	41.2	83.6	68.6	156.4
LSTM	**5.5**	15.5	**107.2**	**200.6**	40.8	82.8	61.1	**139.3**
LSTM-Full	5.6	**15.3**	109.2	203.1	**36.1**	**76.9**	**60.7**	140.5

Prediction for different horizons. All metrics are reported in watts.

Horizon	clear		partially cloudy		overcast		all			
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	SS-MAE	SS-RMSE
1-min	5.6	15.3	109.3	203.5	36.4	76.5	60.7	140.5	25.5%	20.8%
2-min	9.1	20.6	160.7	263.2	54.6	92.6	90.2	181.5	16.4%	11.5%
5-min	15.2	30.4	203.0	292.4	87.4	126.5	120.7	206.3	14.4%	10.4%
10-min	21.4	36.8	239.1	321.8	133.7	183.9	153.8	238.5	12.1%	7.7%

Lower is better for the tables

Skill score compared to baseline $SS = 1 - \frac{\mathcal{E}_{forecast}}{\mathcal{E}_{ref}}$



Higher is better for the plots

Forecasting result for a typical day