

Predictive Maintenance of Photovoltaic Panels via Deep Learning

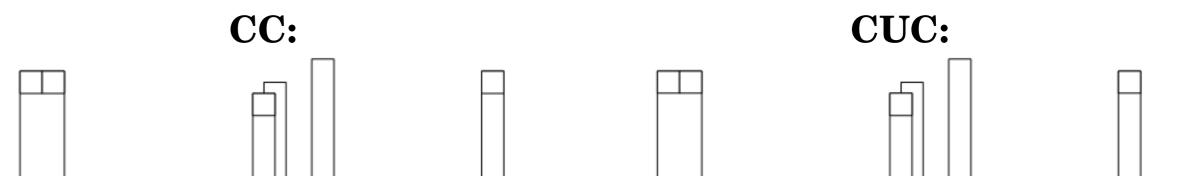
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1. How to detect a malfunctioning photovoltaic (PV) panel?



3. CNN-based predictors

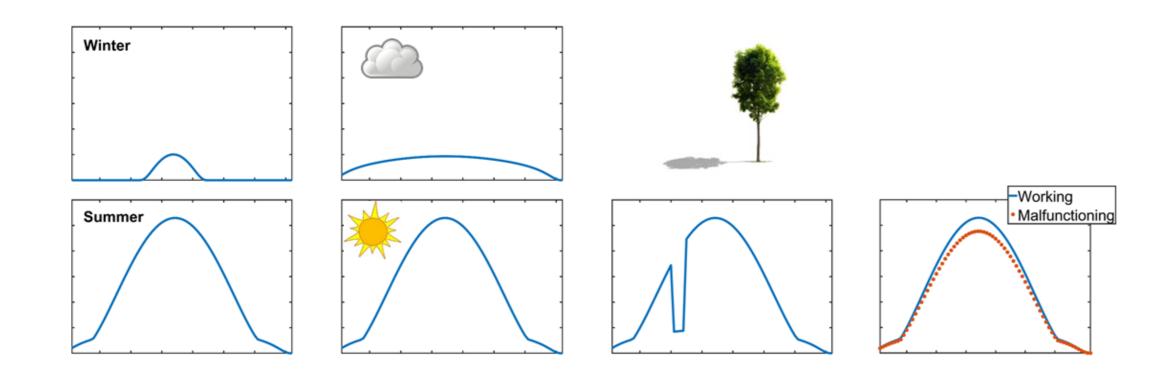
- Convolutional neural network (CNN) with two fully convolutional layers (CC)
- CNN with fully convolutional first layer, unshared convolution for the second layer (**CUC**)

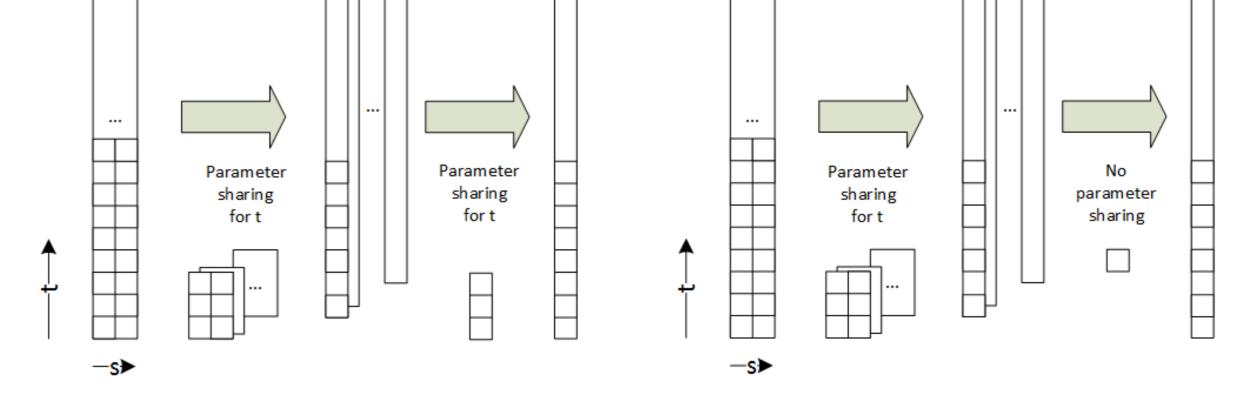


• Input data: Electrical power curve of each PV panel,

P(t,d,s)

- where t = time of the day (in minutes), d = day of the year, s = spatial location of the panel
- The challenge: P(t,d,s) depends on several time-dependent factors:





Input	Convolution	Feature	Convolution	Output	Input	Convolution	Feature	Unshared	Output
image	9@1x3x2	maps	9x3x1	image	image	9@1x3x2	maps	convolution	image
400x2	kernel	9@398x1	kernel	400x1	400x2	kernel	9@398x1	9x1x1	400x1
								kernel	

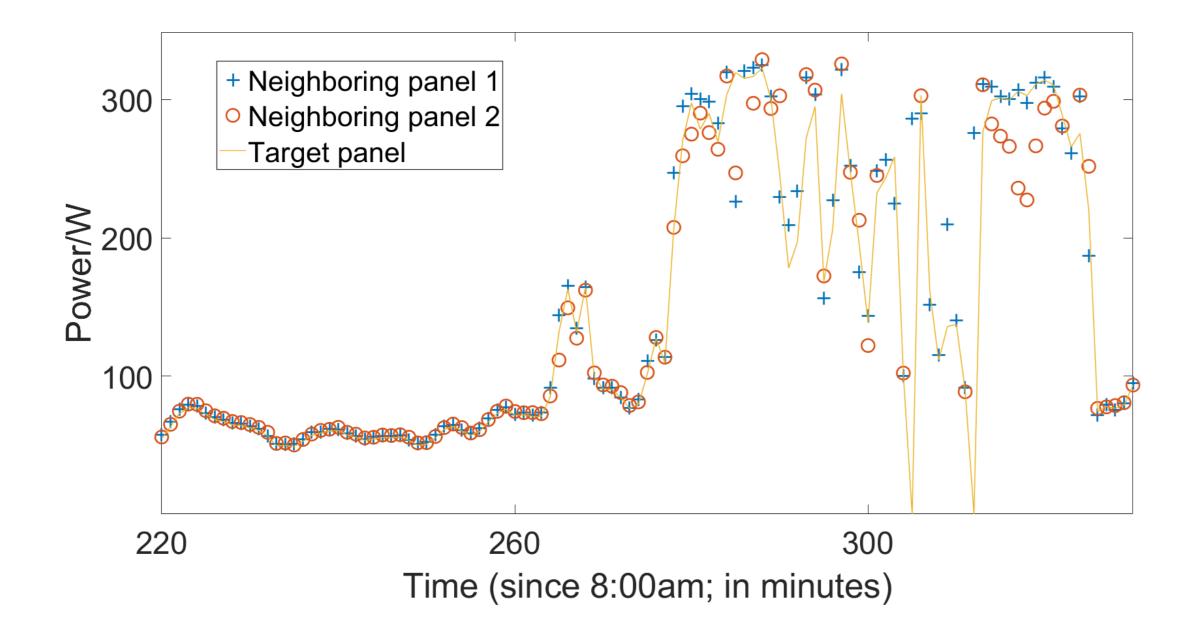
4. Results

• Mean Square errors:

Method	Synthetic test set	Real test set
CC	0.000037	0.002589
CUC	0.000010	0.002346
AVE	0.000421	0.003561

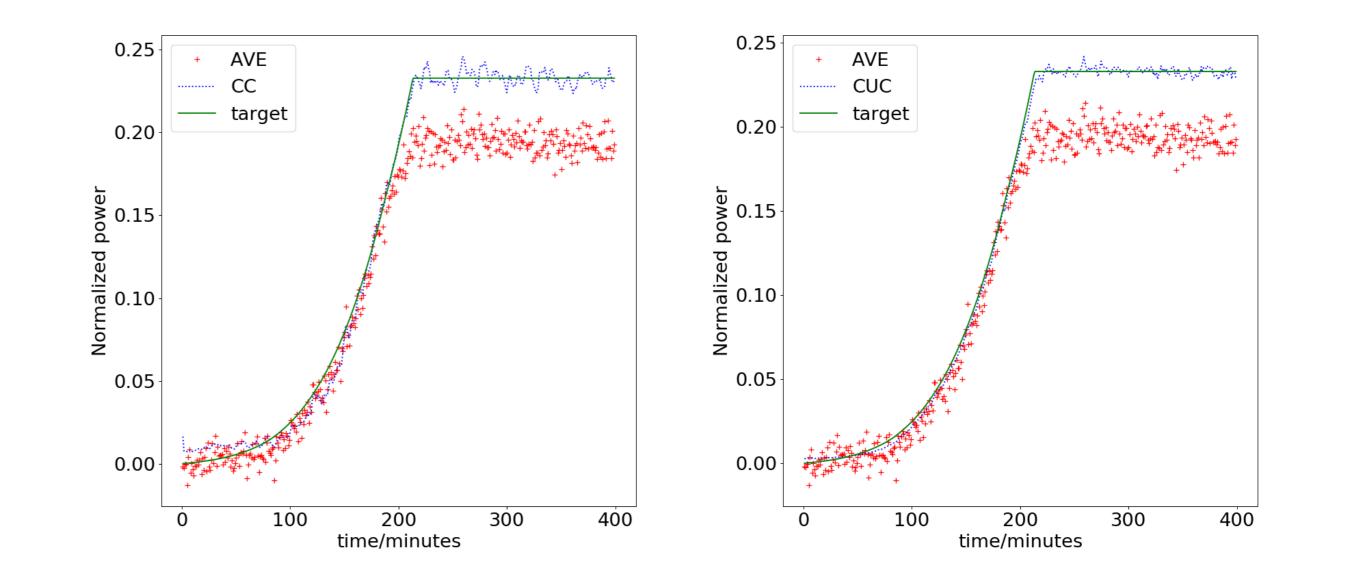
• Samples of actual and estimated power curves - synthetic signal:

• Example of a measured PV panel power curve:

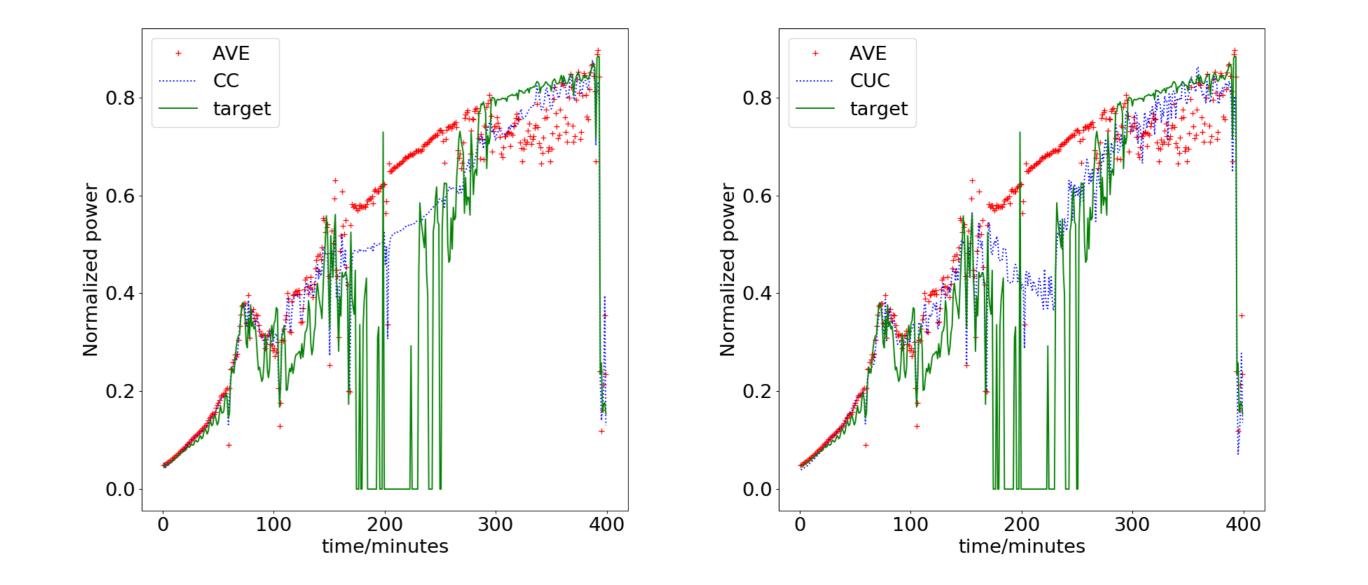




- No training data from malfunctioning panels available
- Find a **predictor** for the power curve using the training data from the panels in its spatial neighborhood, \mathcal{V} ,



• Samples of actual and estimated power curves - real signal:



 $\hat{P}(t, d, s_{target}) = f(P(t, d, s)); s \in \mathcal{V}$

- Compare the **predicted** ($\hat{P}(t, d, s_{target})$) and **actual** power curves ($P(t, d, s_{target})$) \implies a large difference indicates a malfunctioning PV panel
- Benchmark for advanced predictors: average of the two adjacent panels, s_0 and s_1 , (**AVE**),

$$\hat{P}(t, d, s_{target}) = \frac{P(t, d, s_0) + P(t, d, s_1)}{2}$$

5. Conclusion

CNN based methods have potential for predictive maintenance of PV systems
Both CNN-based algorithms (CC and CUC) outperformed the benchmark
CUC algorithm was able to track the impact of regular shadows better

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