Machine learning for supporting automated performance analysis of rooftop PV

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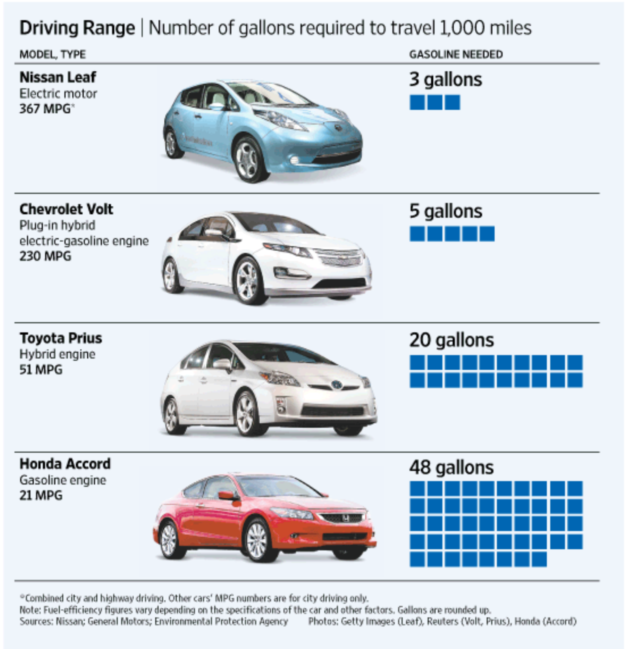
Install and forget

- PV systems can fail in many ways:
  - Delamination, hotspots, connectors, ageing, hailstorms, etc.
- Sub-optimal PV performance can be detrimental for return-on-investment and sustainability targets
- O&M is essential, but often, there are no clear signs if a system is malfunctioning or not
- Huge opportunity for data analytics and large-scale system monitoring

How to quantify performance?

- ~~Efficiency~~
- Yield per installed capacity (kWh/W_p)?



How to quantify performance?

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Typical building applications vs. STC

- Non-optimal tilt and orientation
- Low light conditions
- Temperature effects
- Partly shaded sites
- Year-to-year variability

How to quantify performance?

- ~~Efficiency~~
- ~~Yield per installed capacity (kWh/Wp)~~
- Performance ratio (PR)

Performance ratio

Tool for performance assessment:

$$\mathrm{PR} = \frac{P_{site\ measured}}{P_{STC} * \left(\frac{G_{site\ measured}}{G_{STC}}\right)}$$

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Temperature, Degradation, Incident angle, Spectral properties etc.

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← Measured power

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← Measured power

← STC power corrected with actual irradiance

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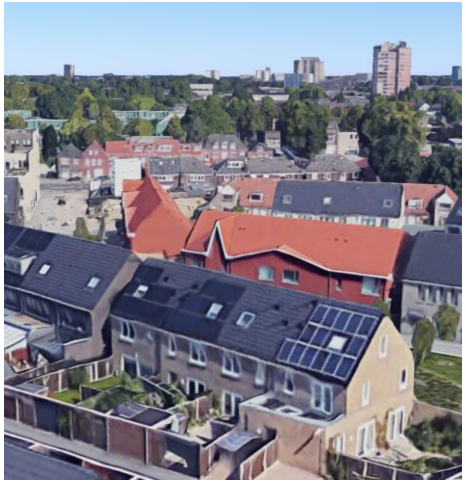
Available data:

On site:

- $P_{site\ measured}$ [W]
- Site details (Tilt, orientation, etc)



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Available data:

On site:

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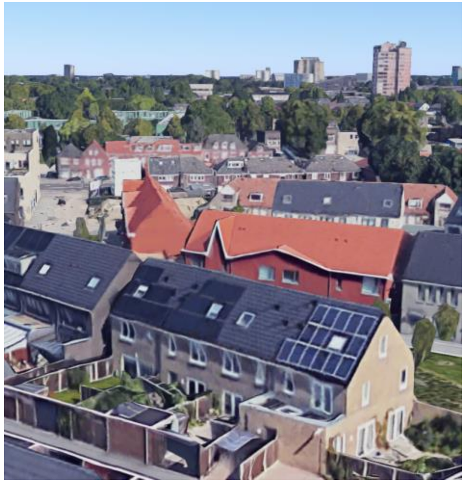
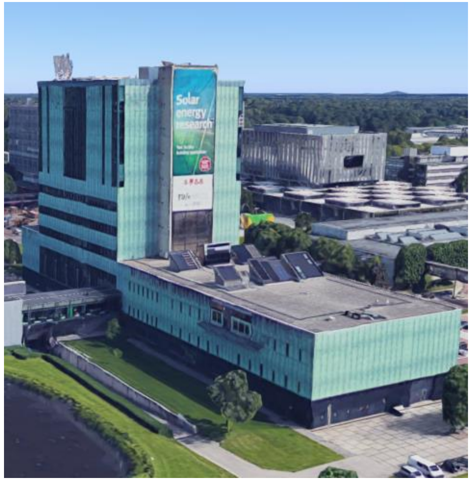
At TU/e Solar Measurement Station:

- Irradiation data (GHI,DNI, DHI)
- Solar position (Azimuth, Zenith)





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Performance ratio

Tool for performance assessment:

$$PR = \frac{P_{site\ measured}}{P_{STC} * \left(\frac{G_{site\ measured}}{G_{STC}}\right)} = \frac{\frac{P_{site\ measured}}{G_{site\ calculated}}}{\frac{P_{STC}}{G_{STC}}} = \frac{\eta_{site\ measured}}{\eta_{STC}}$$

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We intend to use it to compare real life on-site performance of CIGS and C-Si.

Available data:

On site:

- $P_{site\ measured}$ [W]
- Site details (Tilt, orientation, etc)

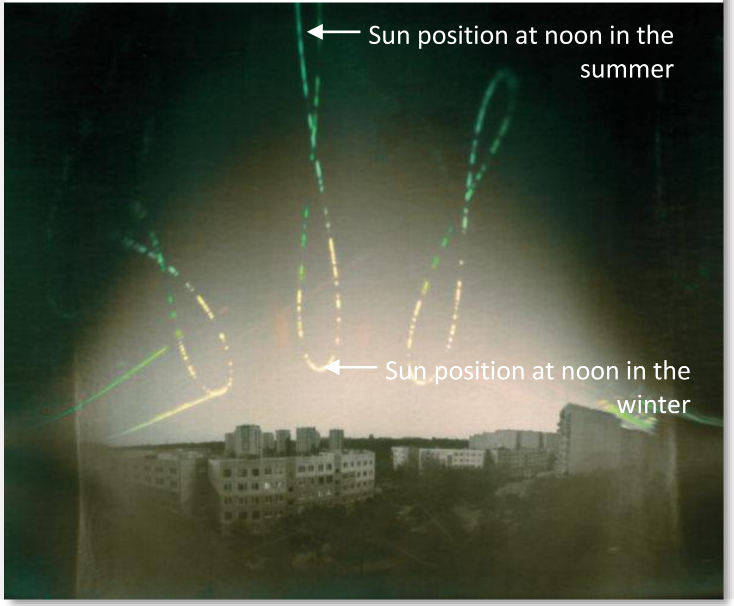
At TU/e Solar Measurement Station:

- Irradiation data (GHI,DNI, DHI)
- Solar position (Azimuth, Zenith)

→ $G_{site\ calculated}$

Visualization

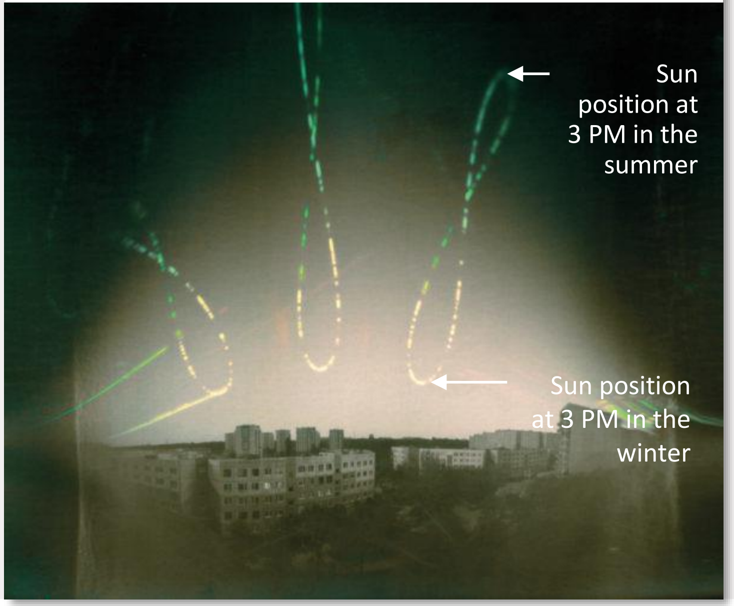
Analemma



Daily sun path

Visualization

Analemma

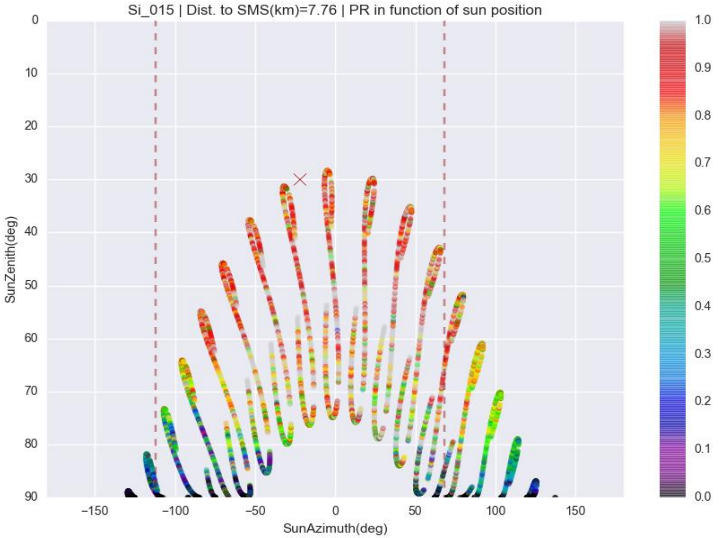


Daily sun path

Visualization

Analemma

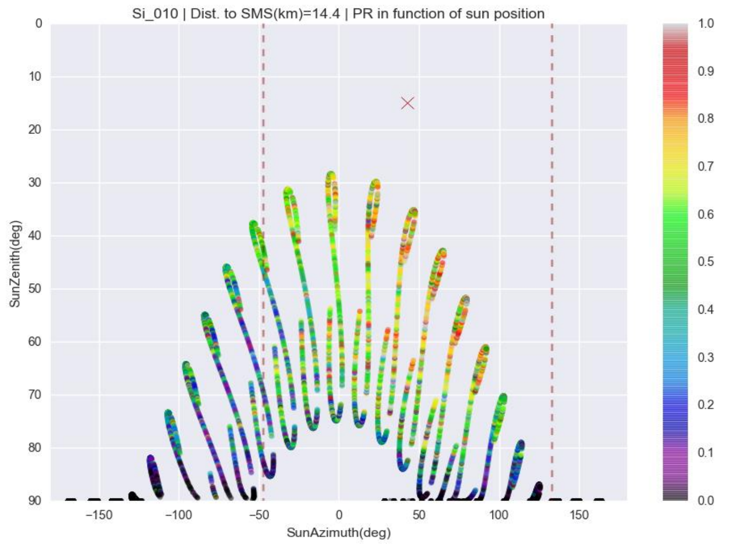
Analemma - PR



Visualization

Analemma

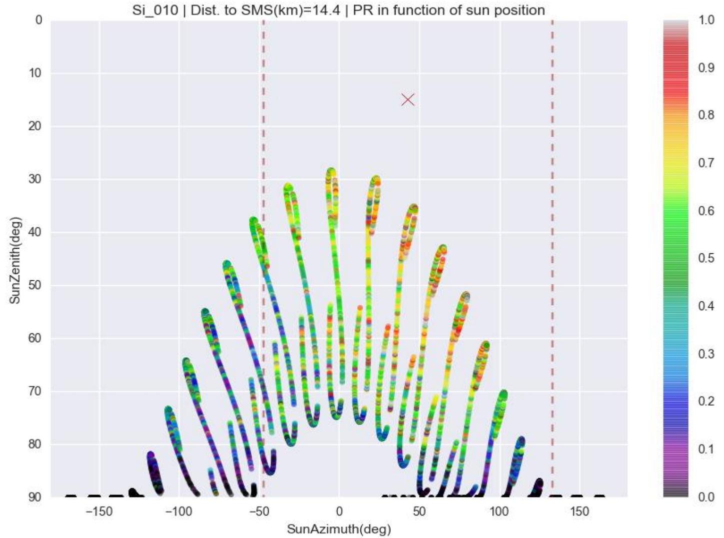
Analemma - PR on a shaded site



Visualization

Analemma

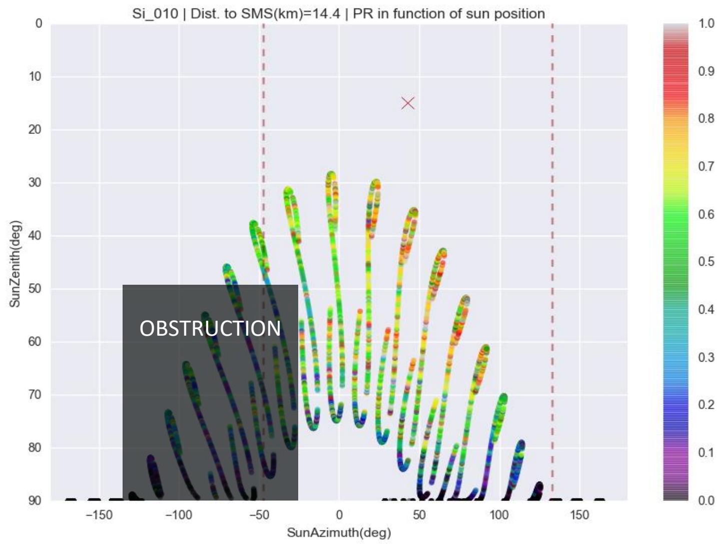
Analemma - PR on a shaded site



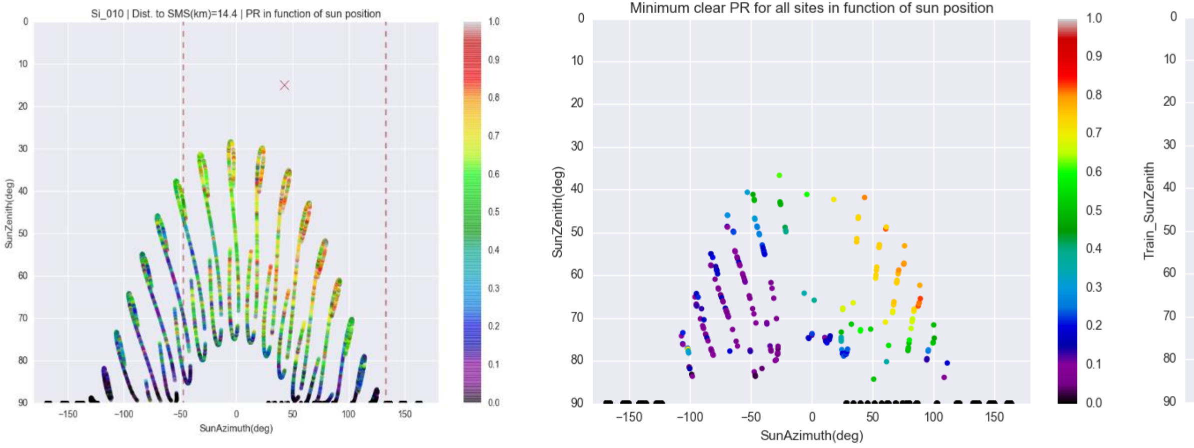
Visualization

Analemma

Analemma - PR on a shaded site

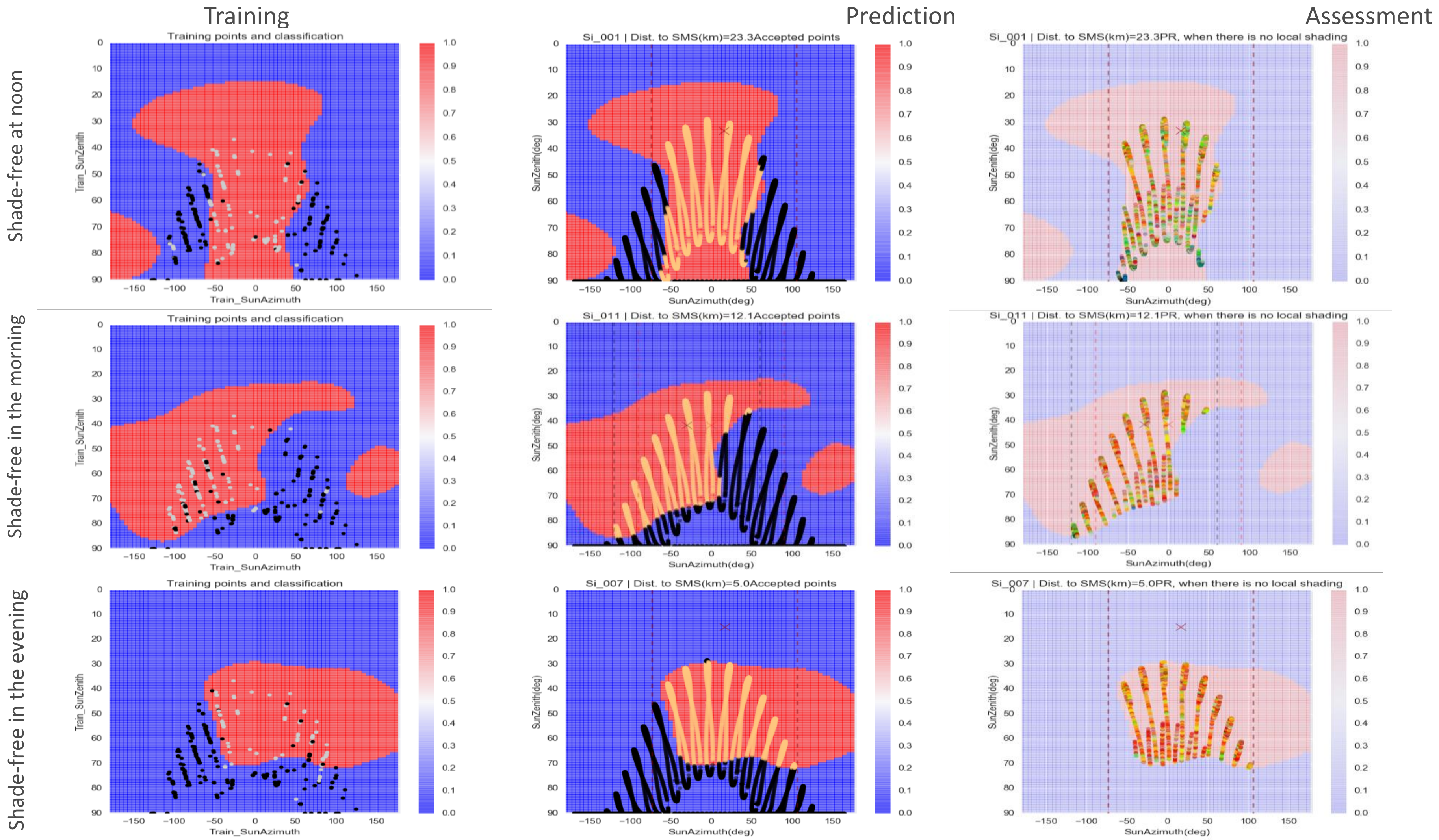


Evaluate datapoints without local shading



<u>Performance Ratio</u>

$$PR = \frac{\frac{P_{site\ measured}}{G_{site\ calculated}}}{\frac{P_{STC}}{G_{STC}}} = \frac{\eta_{site\ measured}}{\eta_{STC}}$$

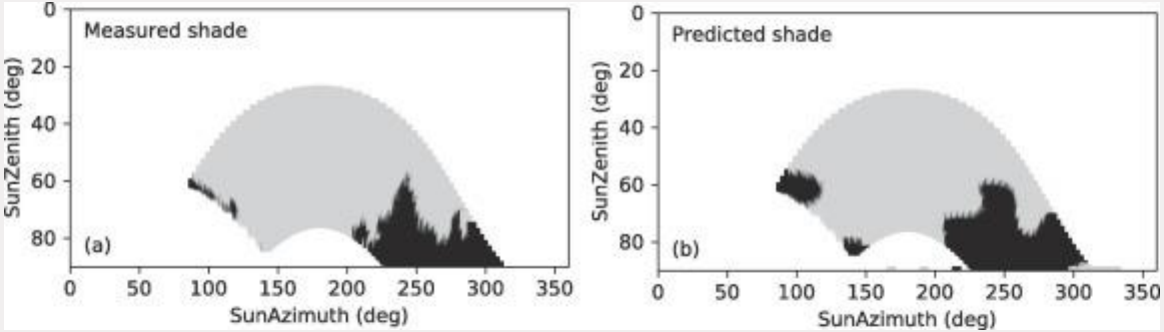


Training
Prediction
Assessment
Shade-free at noon
Shade-free in the morning
Shade-free in the evening
Training points and classification
Train_SunZenith
Train_SunAzimuth
Si_001 | Dist. to SMS(km)=23.3Accepted points
Si_001 | Dist. to SMS(km)=23.3PR, when there is no local shading
Si_011 | Dist. to SMS(km)=12.1Accepted points
Si_011 | Dist. to SMS(km)=12.1PR, when there is no local shading
Si_007 | Dist. to SMS(km)=5.0Accepted points
Si_007 | Dist. to SMS(km)=5.0PR, when there is no local shading
SunZenith(deg)
SunAzimuth(deg)

Conclusions

- ▶ The proposed method is scalable and is ready to be integrated in automated workflows
  - Works with only data that is commonly available
  - No human intervention needed

- ▶ Support vector machines (SVM) are powerful for pattern detection in problems with geometrical features



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Thank you!

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An unsupervised method for identifying local PV shading based on AC power and regional irradiance data

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ABSTRACT

Monitored power output data of photovoltaic (PV) installations is increasingly used for purposes such as fault detection and performance studies of distributed PV systems. The value of such datasets can increase significantly when they are paired with information about local irradiance and shading conditions, especially in urban environments. However, on-site irradiance measurements are seldom performed for small or medium-sized rooftop PV installations. This paper proposes a novel method to identify locally shaded periods of PV installations, using only measured AC power, regional irradiance data and basic information about the sites (i.e. module tilt, orientation and nominal power) as inputs. The proposed three-step method uses machine learning techniques and a grey-box PV performance prediction model to classify the visible sky hemisphere of a PV installation to obstructed and unobstructed areas. Detailed results of a moderately-shaded residential PV site in the Netherlands are shown to illustrate the working principles of the method. Finally, a successful comparison with on-site shade measurements is carried out and the ability of the method to detect shade from nearby objects is illustrated.

1. Introduction

In 2017, almost as much solar was installed in one year (99.1 GW) as the world had installed in total by 2012 (100.9 GW). This led to a total global solar power capacity of over 400 GW in 2017 (SolarPower Europe, 2018). In Europe, more than 44% of the new installations in 2017 were on rooftops where shading effects of the urban environment are not always avoidable. Whereas in early PV applications sites were carefully selected to be as shade-free as possible, it is expected that with the decreasing prices of PV systems and the spread of new Building Integrated PV (BIPV) applications, PV will increasingly be installed on surfaces where the effect of shading is of considerable importance (Zomer et al., 2016; Zomer and Rüther, 2017).

Cloud-based monitoring services are routinely used to record the power output of distributed PV systems (Solórzano and Egido, 2013). In addition to providing feedback to the owners of these systems, there is a substantial potential to exploit such recorded power measurements, both in research and for quality assurance of commercially installed systems. The value of this data can be increased by creating a computational representation of the same PV site, allowing for side-by-side comparisons between the measured and expected performance of the system. However, because plane-of-array irradiance measurements at small or medium-sized PV plants are seldom performed (Nespoli and Medici, 2017), it is difficult to correlate PV output with actual site-specific irradiance conditions. Due to this information mismatch in relation to local shading conditions, causal relationships between system/site conditions and PV power output are hard to establish, which diminishes the value of these datasets.

PV monitoring systems usually record output in terms of the installation's AC power. This means that the influence of power systems such as inverters and converters needs to be taken into account in subsequent analyses. Lack of information about the characteristics of these power systems can be a significant source of uncertainty in PV performance analyses. An additional challenge is that, depending on the architecture of the power systems of a PV installation, the reduction in output due to (partial) shading is not linearly related to the shaded fraction. Uncertainty in the knowledge of the shading conditions of a specific PV site can therefore cause disproportionally large prediction errors especially if the power system of the PV site is unknown, or not modeled explicitly. To determine if a PV system is operating as expected, it is therefore of high importance to have an accurate estimate of when and to what extent a site is shaded. This need for detecting locally shaded periods of PV installations has been recognized in three different areas:

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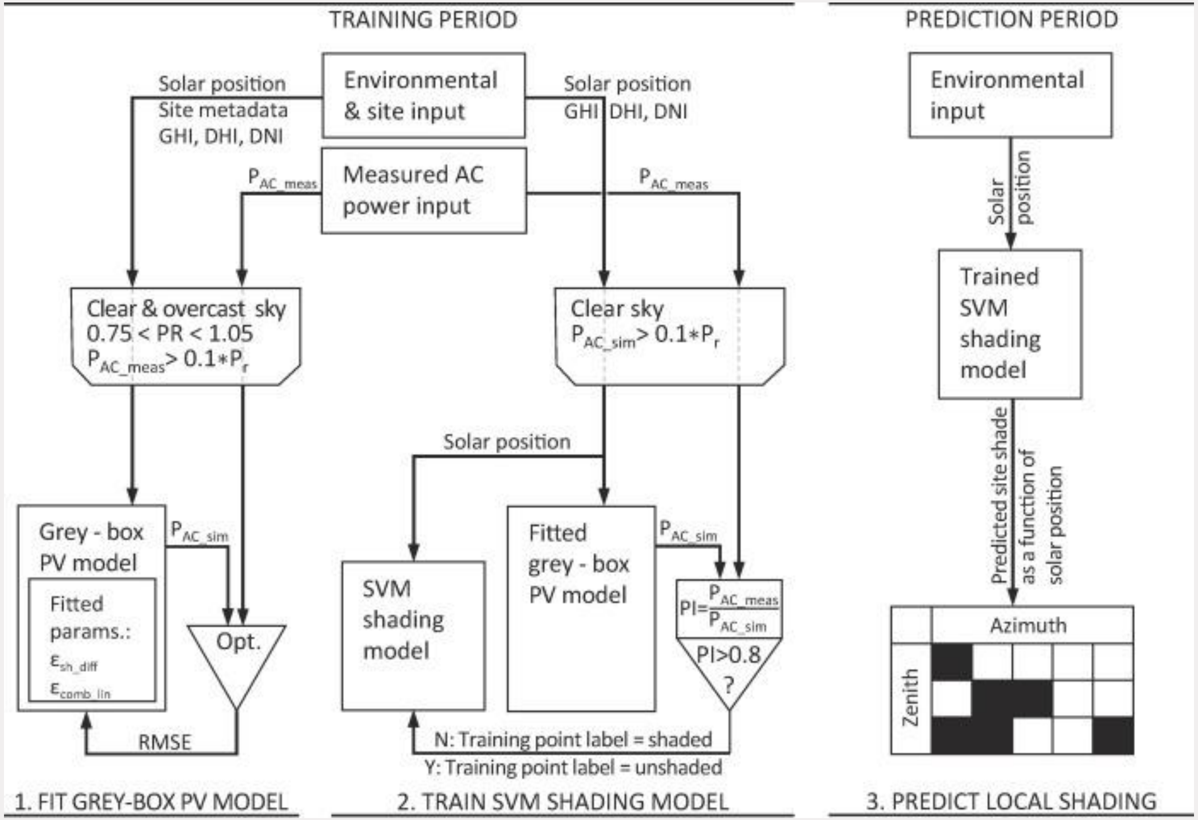
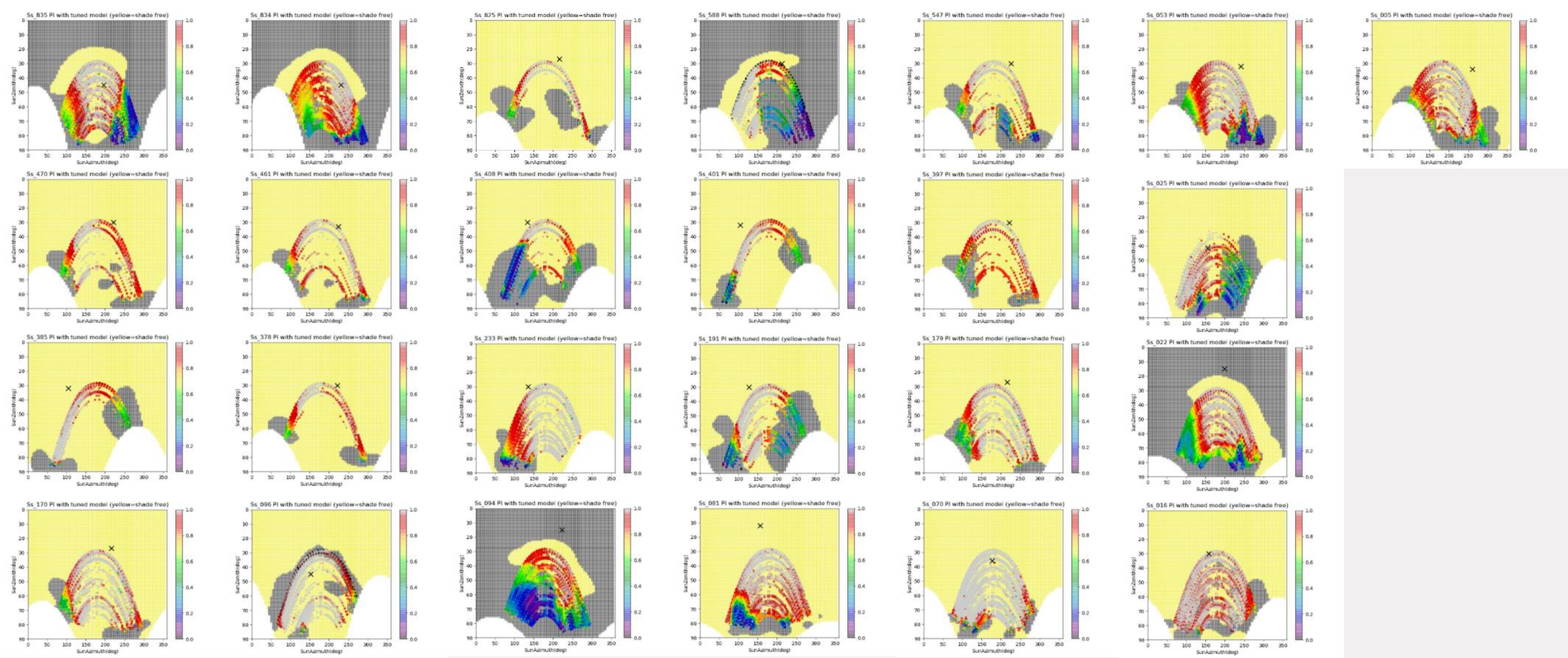

TRAINING PERIOD
PREDICTION PERIOD
Environmental & site input
Solar position
Site metadata
GHI, DHI, DNI
Solar position
GHI, DHI, DNI
Measured AC power input
P_AC_meas
P_AC_meas
Clear & overcast sky
0.75 < PR < 1.05
P_AC_meas > 0.1*P_r
Clear sky
P_AC_sim > 0.1*P_r
Solar position
Grey - box PV model
Fitted params.:
ε_sh_diff
ε_comb_lin
P_AC_sim
Opt.
RMSE
SVM shading model
Fitted grey - box PV model
P_AC_sim
PI=P_AC_meas/P_AC_sim
PI>0.8 ?
N: Training point label = shaded
Y: Training point label = unshaded
Environmental input
Solar position
Trained SVM shading model
Predicted site shade as a function of solar position
Azimuth
Zenith
1. FIT GREY-BOX PV MODEL
2. TRAIN SVM SHADING MODEL
3. PREDICT LOCAL SHADING

c-Si sites



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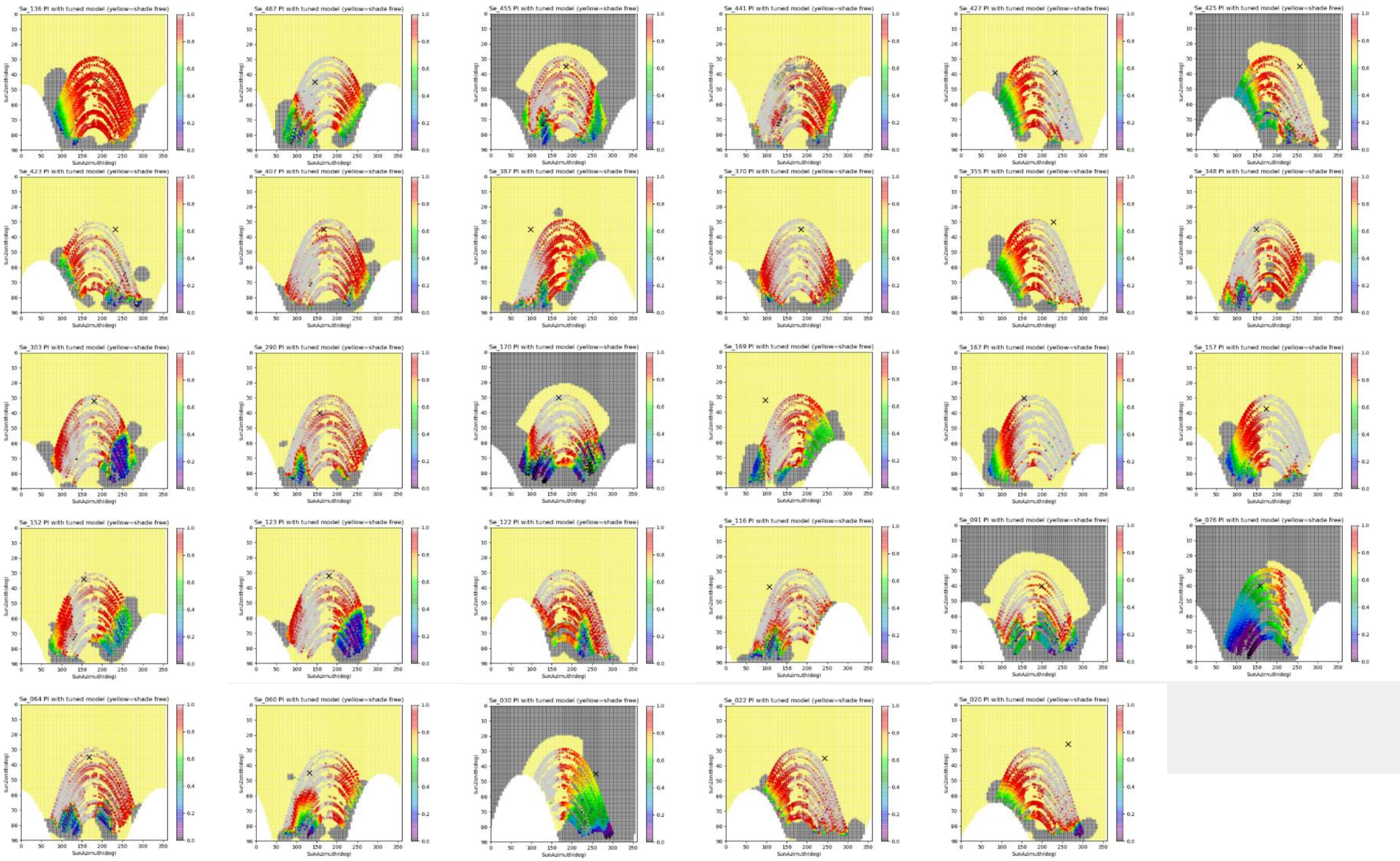
CIGS sites


Se_136 PI with tuned model (yellow=shade free)
Se_467 PI with tuned model (yellow=shade free)
Se_455 PI with tuned model (yellow=shade free)
Se_441 PI with tuned model (yellow=shade free)
Se_427 PI with tuned model (yellow=shade free)
Se_425 PI with tuned model (yellow=shade free)
Se_423 PI with tuned model (yellow=shade free)
Se_407 PI with tuned model (yellow=shade free)
Se_387 PI with tuned model (yellow=shade free)
Se_370 PI with tuned model (yellow=shade free)
Se_355 PI with tuned model (yellow=shade free)
Se_348 PI with tuned model (yellow=shade free)
Se_303 PI with tuned model (yellow=shade free)
Se_290 PI with tuned model (yellow=shade free)
Se_170 PI with tuned model (yellow=shade free)
Se_169 PI with tuned model (yellow=shade free)
Se_167 PI with tuned model (yellow=shade free)
Se_157 PI with tuned model (yellow=shade free)
Se_152 PI with tuned model (yellow=shade free)
Se_123 PI with tuned model (yellow=shade free)
Se_122 PI with tuned model (yellow=shade free)
Se_116 PI with tuned model (yellow=shade free)
Se_091 PI with tuned model (yellow=shade free)
Se_076 PI with tuned model (yellow=shade free)
Se_064 PI with tuned model (yellow=shade free)
Se_060 PI with tuned model (yellow=shade free)
Se_030 PI with tuned model (yellow=shade free)
Se_022 PI with tuned model (yellow=shade free)
Se_020 PI with tuned model (yellow=shade free)
SunZenith(deg)
SunAzimuth(deg)