Quantifying soiling losses for an industrial-scale photovoltaic plant

A project for Nispera AG.

{Propulsion}

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Introduction to the team

Daniel Gisler

- MSc Geography at University of Zurich
- Several years of working experience as a consultant and data analyst in real estate field
- Looking for projects (also open source) and part time positions

Konstantinos Kirtsonis

- MEng Civil - Structural Engineering
- Experience working with Geospatial data and operating systems
- Searching for a position/internship as a Data Scientist

Dave Lonsdale

- MEng Manufacturing Engineering at University of Cambridge (UK)
- Experienced strategy consultant in telecoms industry
- Managed and executed commercial and technical analytical projects
- Looking for opportunities in Data Science field

Business problem: quantify the energy losses due to *dirty* panels

Soiling:	slow accumulation of dirt, dust etc. on panels leading to energy losses
Range:	3-39% per annum observed in Chile
Locally:	~3% per annum in Atacama desert

Photovoltaic plant - Atacama desert

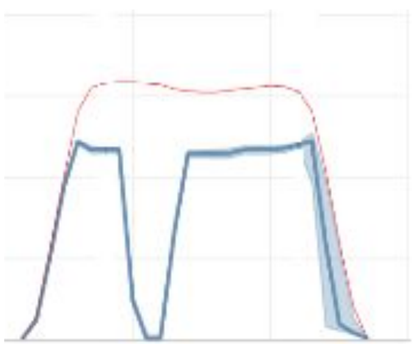
- Peak power: 100 MWp
- 0.4% of national installed capacity

A surprisingly difficult problem to answer using indirect data
=> no commercial solution in the market

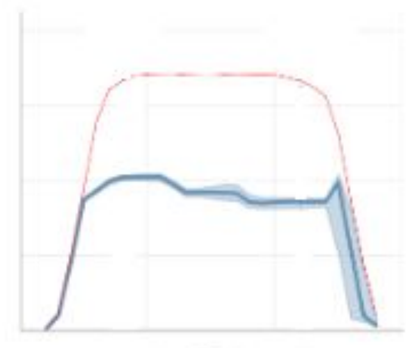
1: Cordero, R.R., Damiani, A., Laroze, D. et al. Effects of soiling on photovoltaic (PV) modules in the Atacama Desert. Sci Rep 8, 13943 (2018).

Other factors that decide efficiency of solar panels

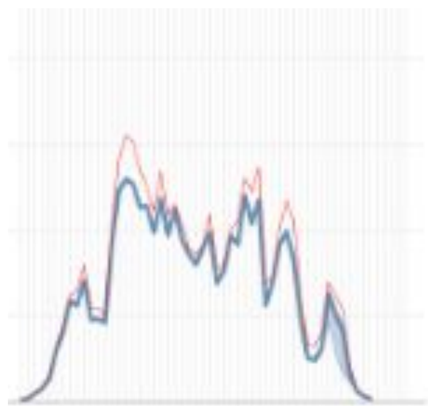
- **Disconnecting:**



- **Underperformance:**



- **Cloudy days:**



- **Technical restrictions:**

-

Temperature effect: As temperature drops the efficiency of the panels improves

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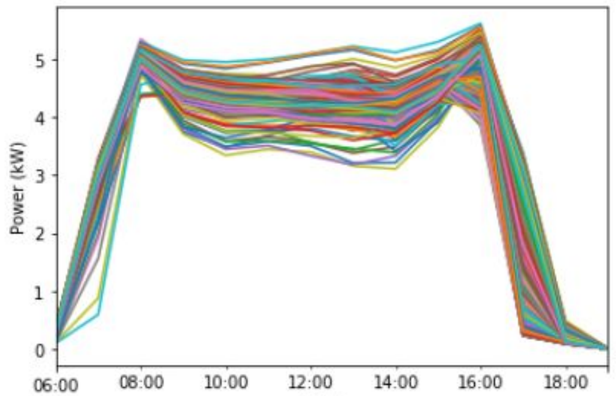
Panel Degradation: Drop in efficiency as panels age (0.5%/year)

Actual energy

Expected energy

How to filter out all those other factors?

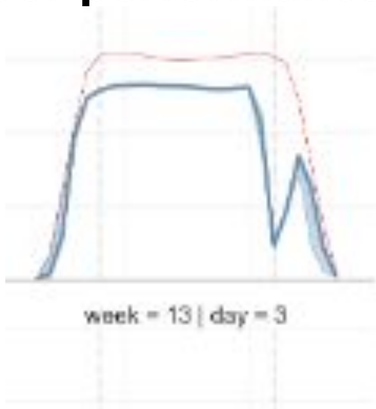
1 string contains 20 solar panels



380 daily string profiles

Good performance:

Poor performance:

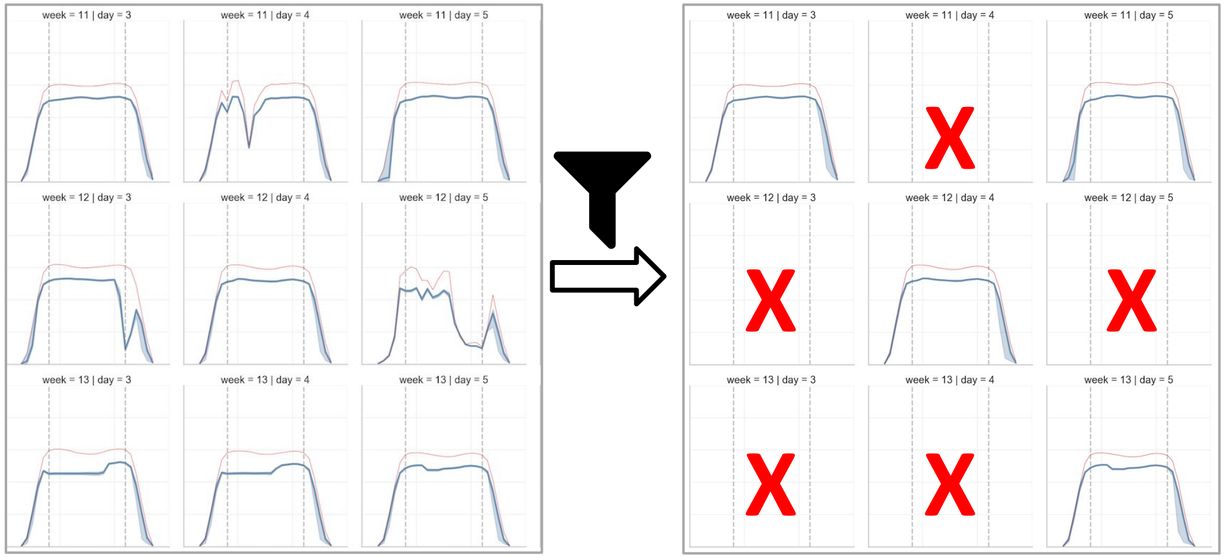


Filtering result:
Selecting good strings and removing the mentioned factors

Actual energy profile
Expected energy profile

Our toolkit filters for good days and good strings, reducing noise

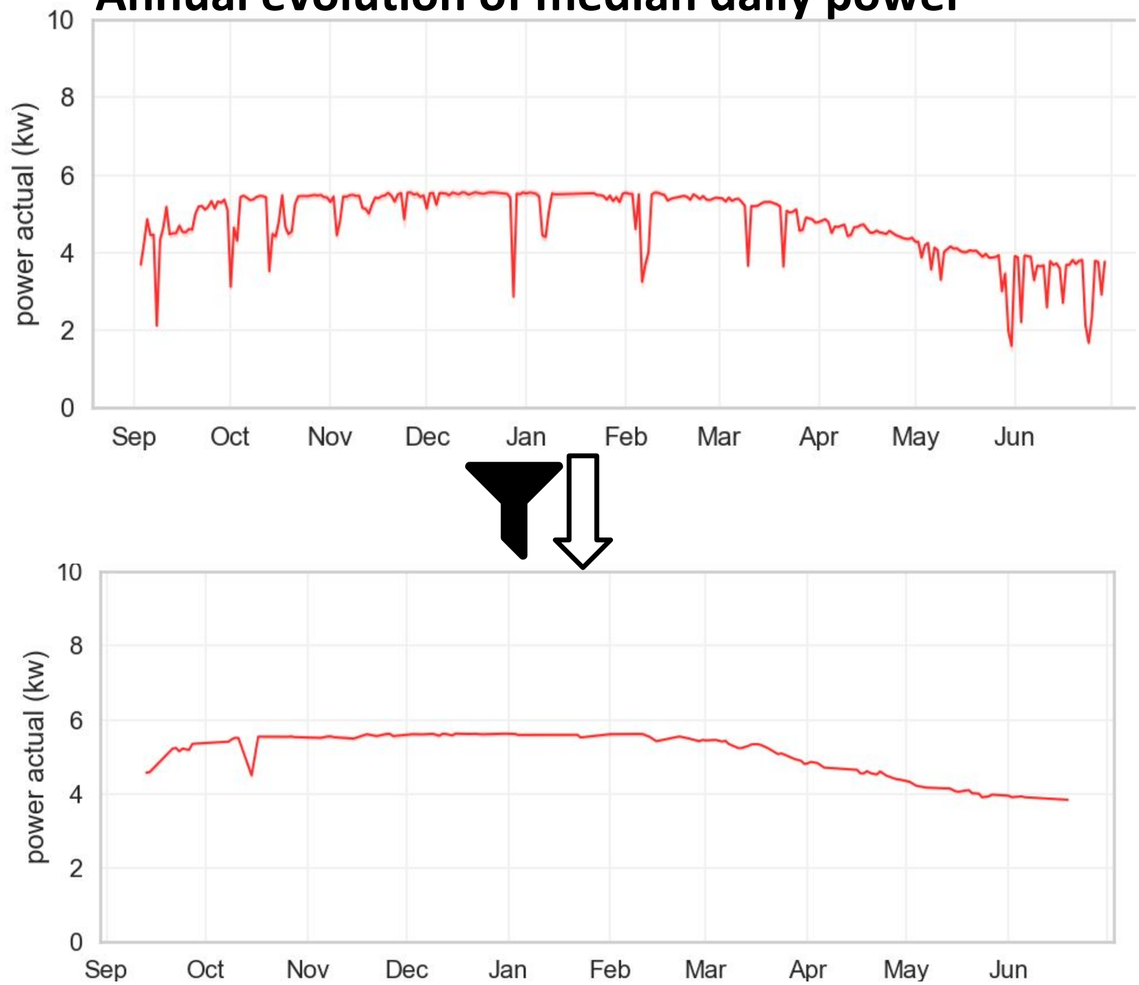
Daily view of irradiance and strings



Automatic filtering of good and bad strings

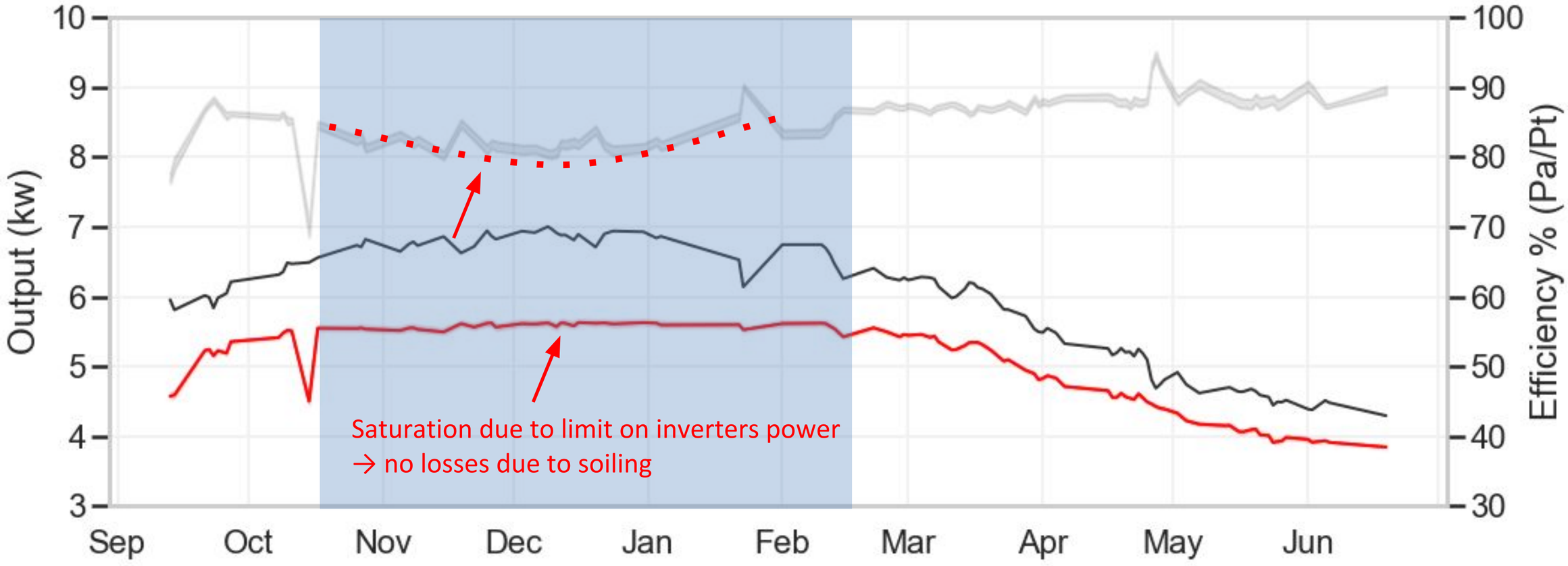
- can easily be applied to other power plants
- a set of different filtering methods to choose
- integration of new methods is possible
- significantly reduces noise in the time-series data

Annual evolution of median daily power [1]

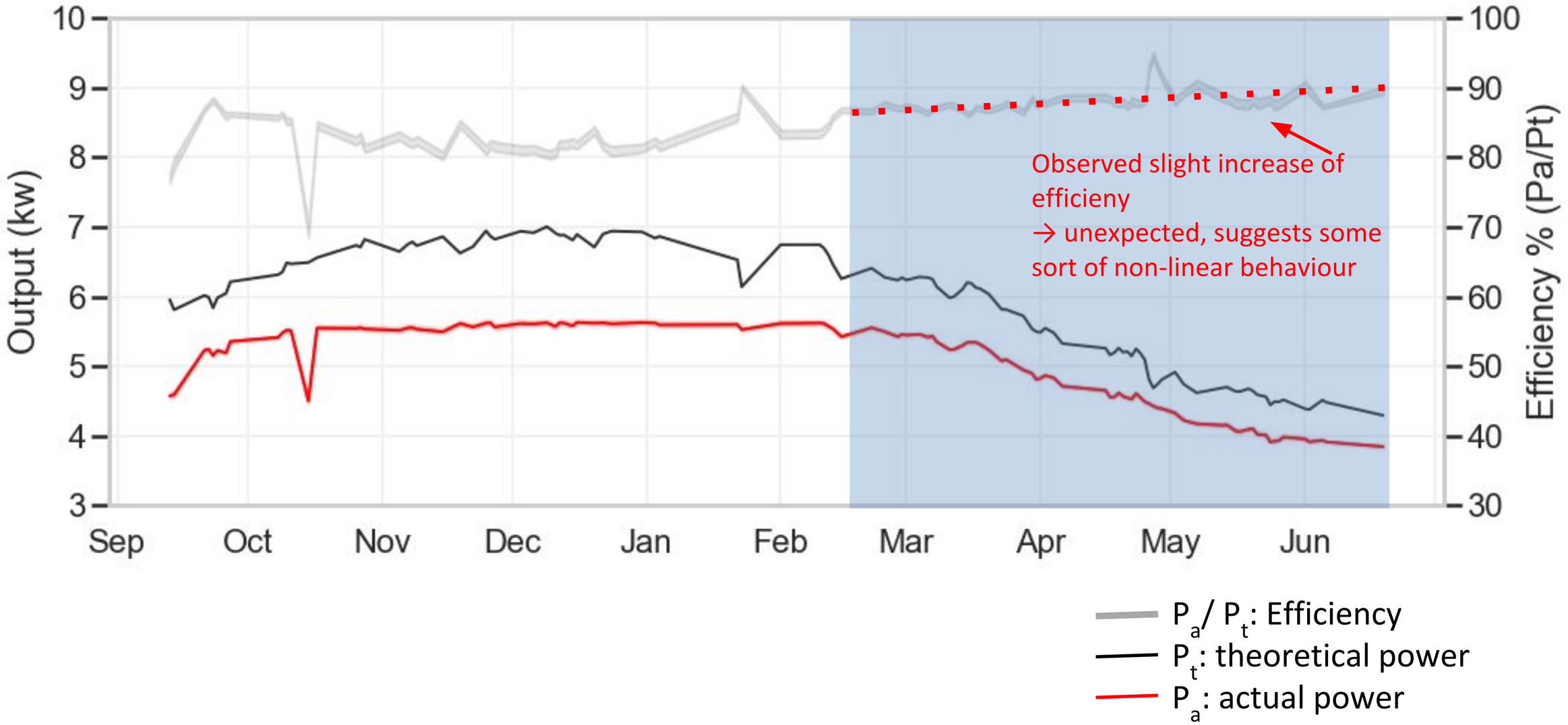


1: with middle-of-day time filter (09:00-16:00)

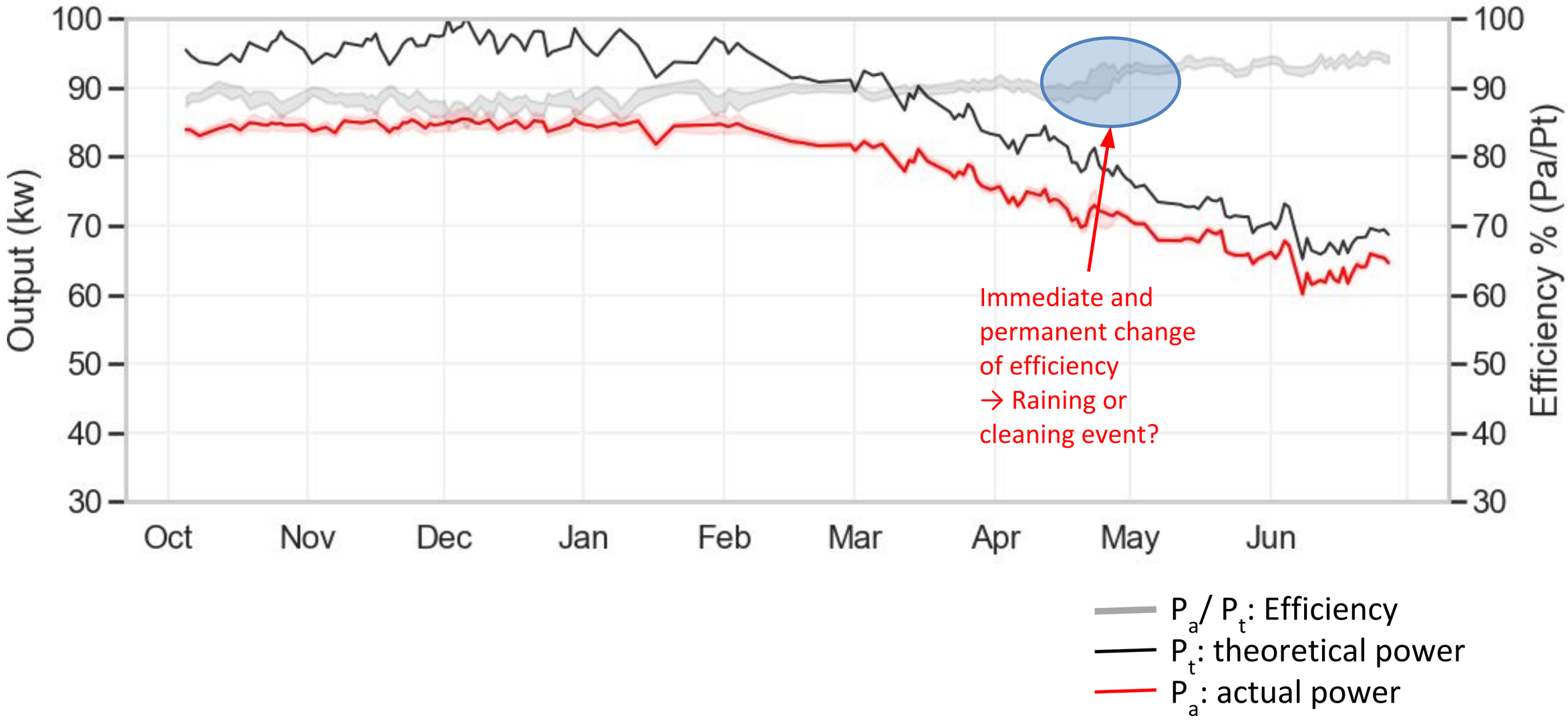
We identified saturation during summer…



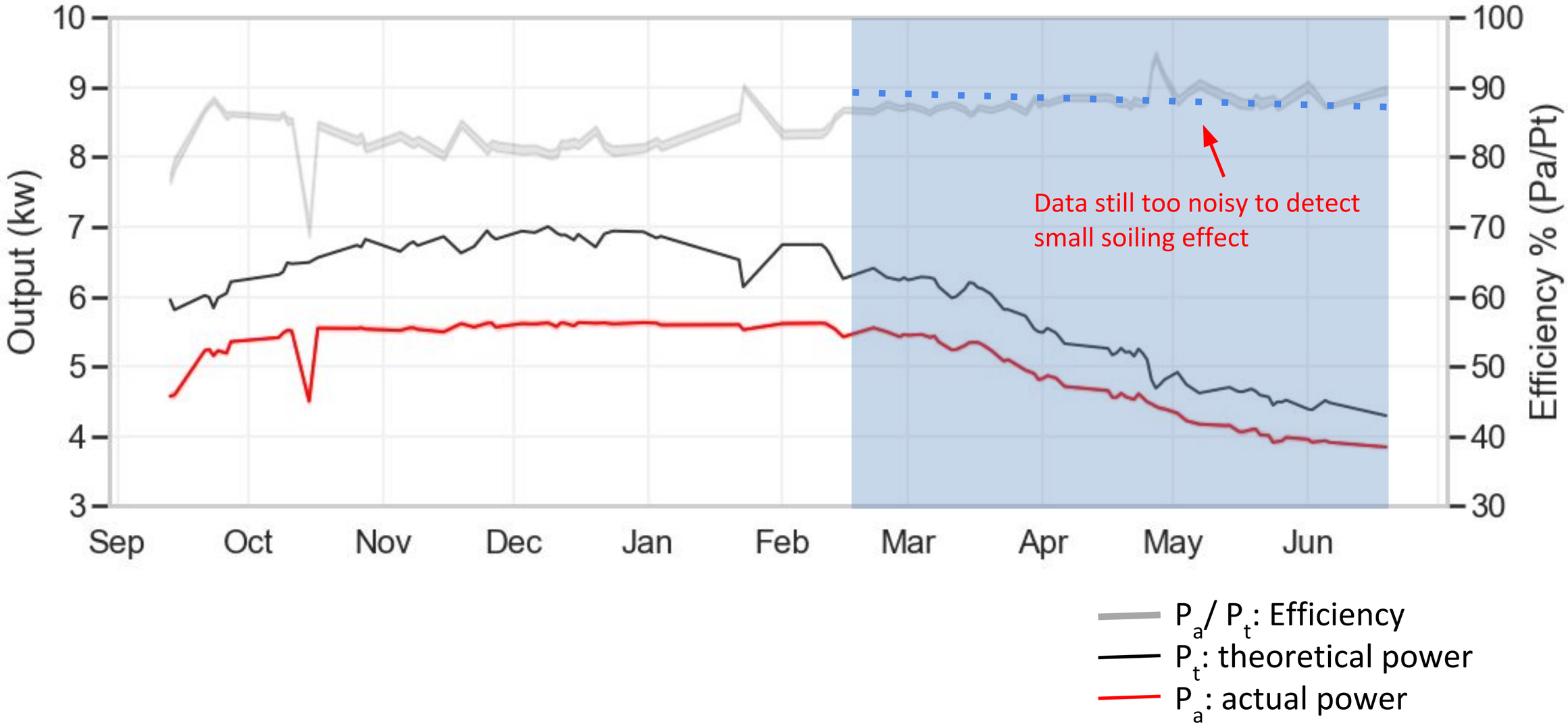
…unexpected non-linear behaviour…



…and a step change in performance…



… but not enough signal to detect soiling



Identified next steps

Calibration:	Plant is currently being cleaned which will provide a baseline reference
More data:	In unsaturated periods (late autumn - early spring)
Non-linearity:	Investigate observation, focusing on temperature parameters
Clustering:	Further develop ML techniques (e.g. time-series clustering)
Toolkit:	Further develop additional physical models

Conclusions

No soiling detected:	Remains a very hard problem, with no indirect-measurement solution offered in the market
Toolkit:	Significantly reduces noise so that trends and events in production efficiency can be observed
Business insights:	• Saturation negates any soiling effect during summer • Possible non-linear effect in winter • Performance improvement identified on plant 2

Thank you!

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