Get more out of existing measurement data – Model-based condition monitoring

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Solarize training course

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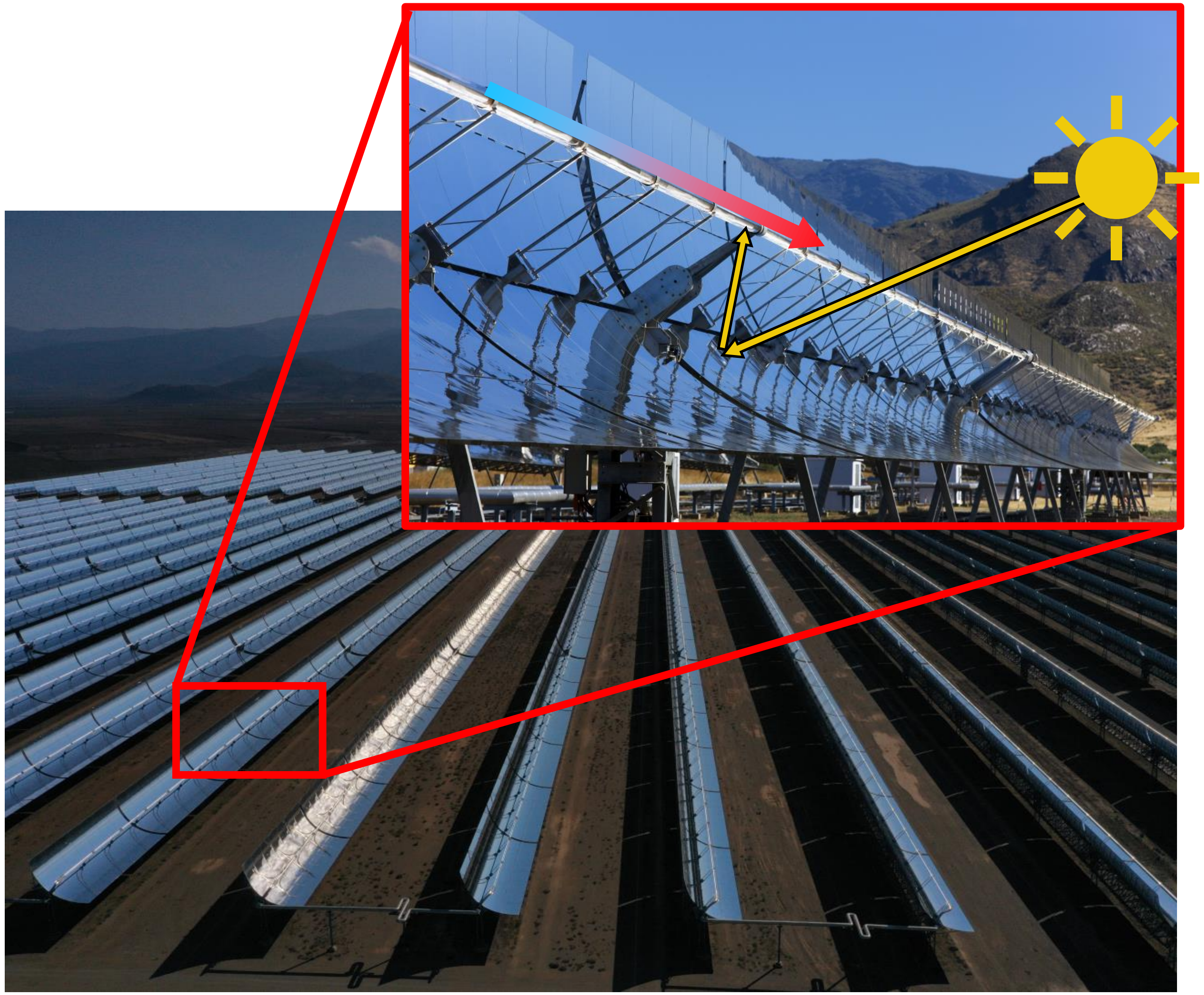
DLR

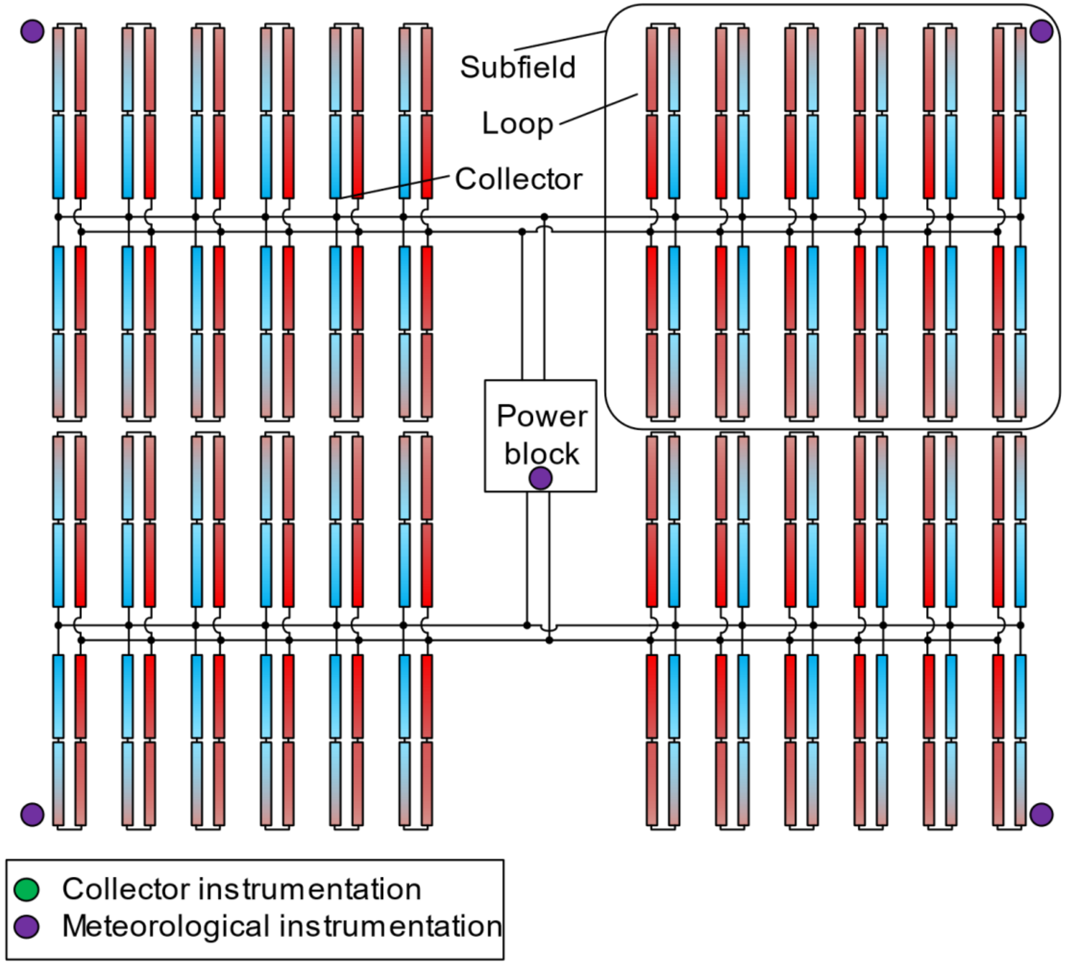
Agenda

- Overview parabolic trough field
- Motivation
  - Condition monitoring with existing measurement instrumentation
- Model-based condition monitoring
  - Deterministic models vs. data-driven approaches
  - Learning representations from raw time series data
  - Application: Representations used for anomaly detection
  - Application: Representations compared to soiling values
- Conclusions
  - High potential for model-based condition monitoring using existing measurement instrumentation

Parabolic trough at Plataforma Solar de Almería
(Owned by the Spanish research center CIEMAT)

Overview parabolic trough field





Overview parabolic trough field
Available measuring equipment

Typical instrumentation

- Flow, pressure, and temperature at solar field and subfield level
- Temperature, inclinometer, and optional sun/tracking sensor at collector level
- Temperature at loop outlet
- Meteo stations: DNI, temperature, wind, pressure, humidity, precipitation
- Maintenance measurements, e.g. mirror cleanliness

Summary

- Approx. 2000 measurement channels in a parabolic trough field
- Spatially distributed in the field (1.5 x 1.5 km²)
- Good conditions for data driven approaches

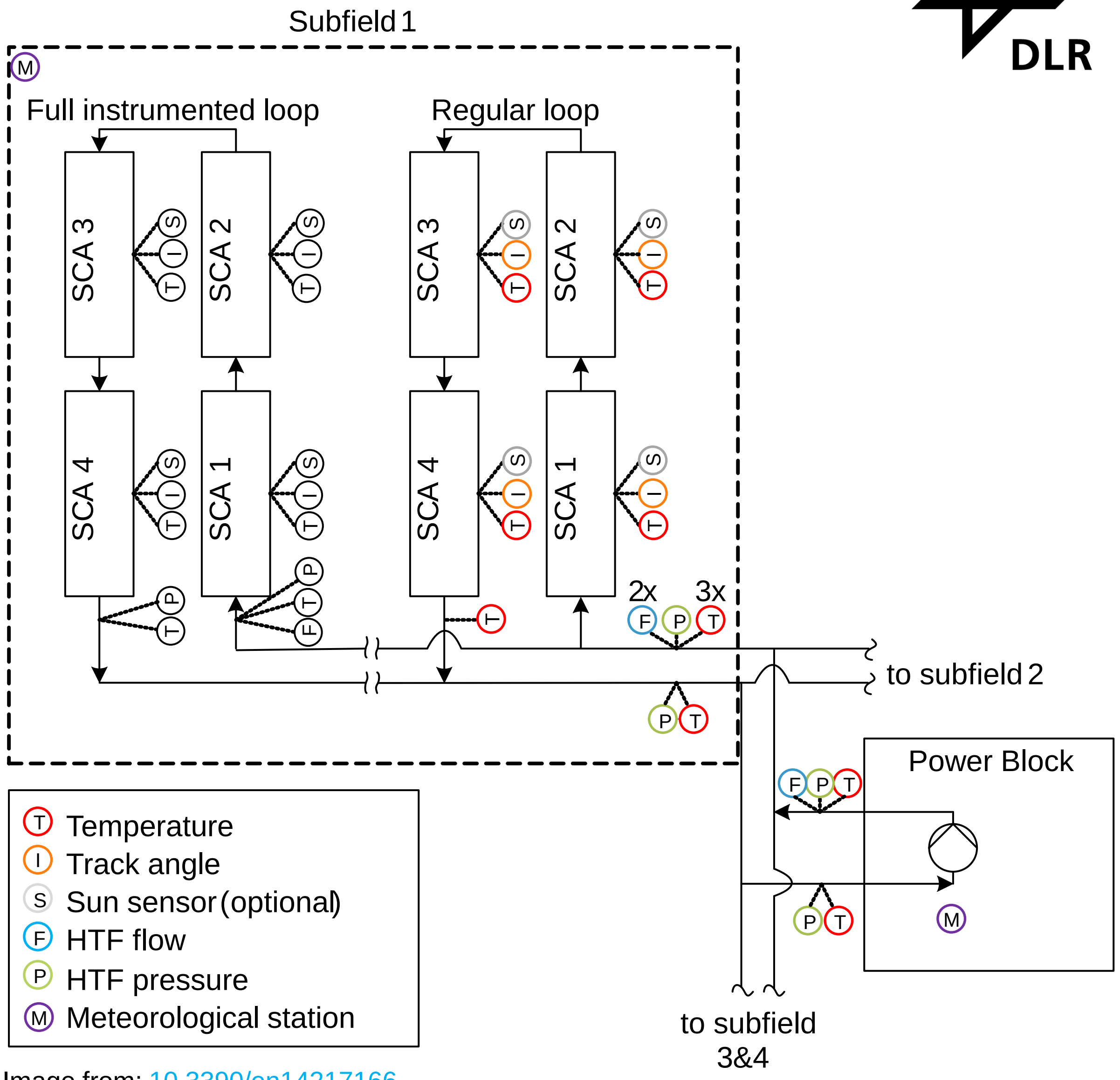


Image from: 10.3390/en14217166.

Motivation
Condition monitoring with existing measurement instrumentation

- Main goals: Increase the solar yield and reduce the costs
- Condition monitoring state of the art
  - Manual inspections, simple signal checks, model based anomaly detection
- Two options for condition monitoring
  - Special measurement equipment for each monitoring task
  - Existing instrumentation + model to calculate a monitoring variable
- Low implementation hurdles, e.g. low cost, no interference with running system
- No additional hardware installation required

[4]

MODEL-BASED CONDITION MONITORING

Solar field condition
Deterministic models vs. data-driven approaches

Power plant layout

Meteo data

Losses

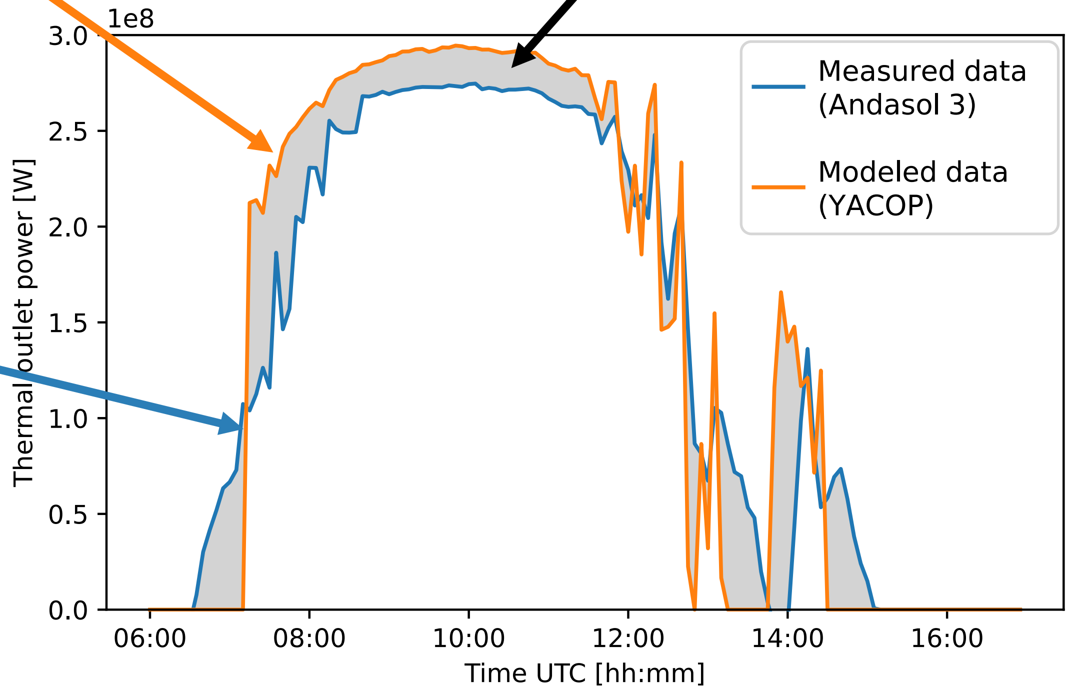
Additional data …

Deterministic power plant model, e.g. YACOP [1]

Gap between is model error + **missing information about solar field condition**

- Option 1: Add more condition measurements
- **Option 2: Use existing time series data + AI to extract the condition**

The real world: Andasol 3

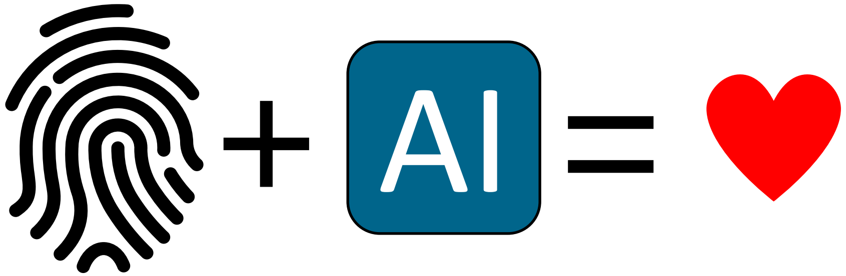


Solar field condition
Which data describes the current plant condition?

Importance

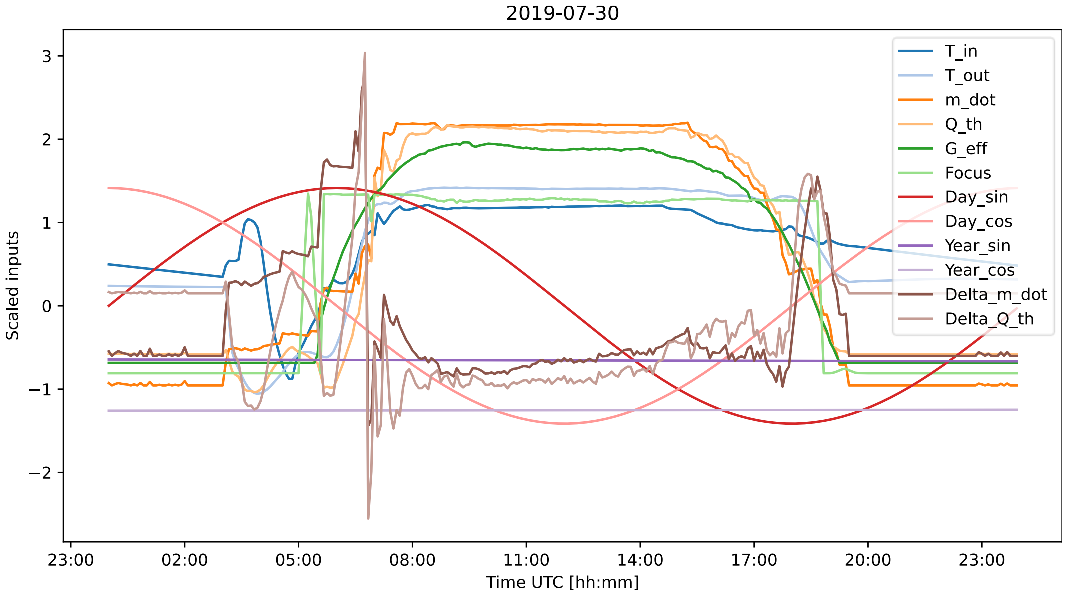
Effect	Operation data
Soiling	▪ Thermal outlet power reduced $\dot{Q}_{th,out}$ ▪ Mass flow and HTF temperature affected
Dumping	▪ Thermal outlet power reduced $\dot{Q}_{th,out}$ ▪ Reduced mass flow, reduced focus
Loop under maintenance	▪ Thermal outlet power reduced $\dot{Q}_{th,out}$ ▪ Very low HTF temperature ▪ No tracking
Heat loss	▪ Thermal outlet power reduced $\dot{Q}_{th,out}$ ▪ Reduced HTF temperature ▪ Possibly mass flow affected ▪ Fast cooling during off-sun periods
Faulty tracking	▪ Thermal outlet power reduced $\dot{Q}_{th,out}$ ▪ Reduced HTF temperature ▪ Possibly mass flow affected

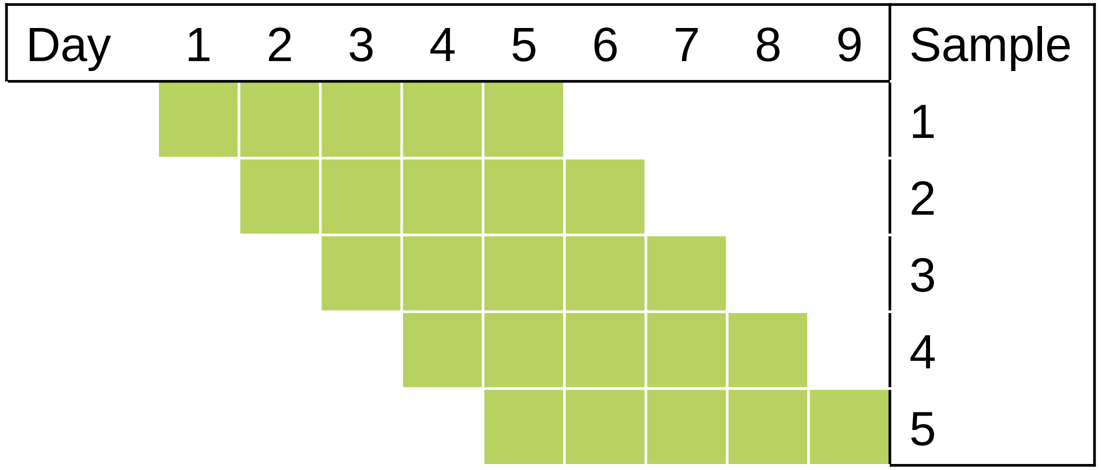
All effects
- Reduce thermal outlet power
- Are affected by the irradiance
- Occur in different forms
- **Leave patterns in the measurement data**



Methods
Raw time series data

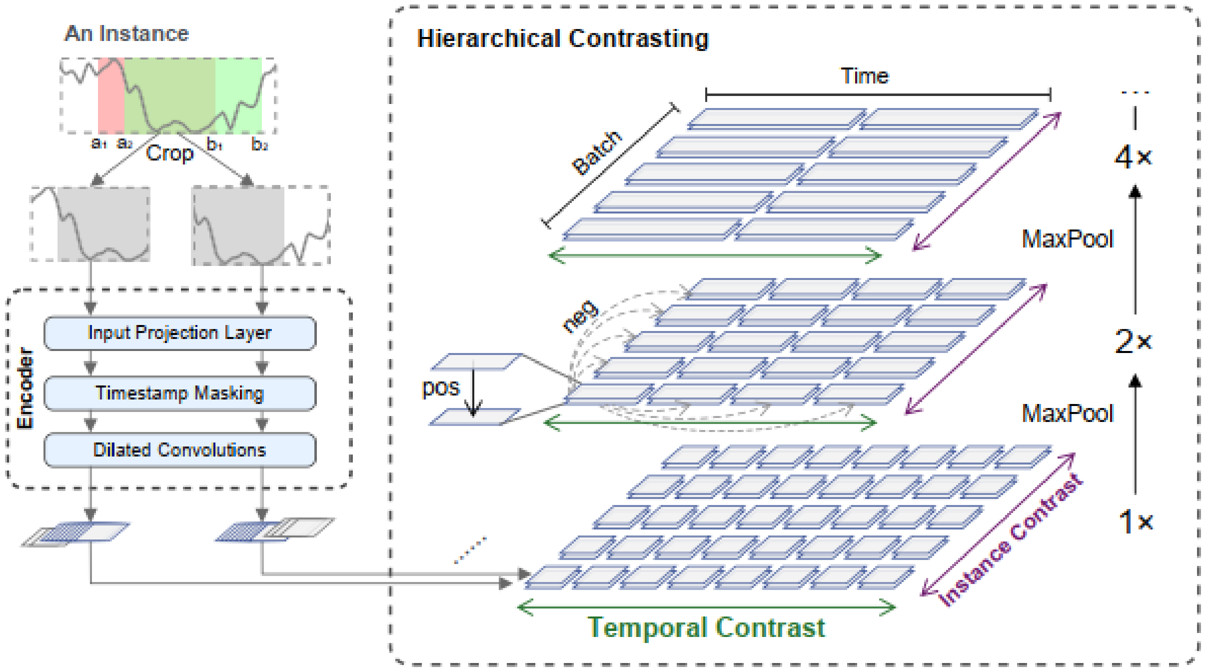
- Raw time series data from Andasol 3 power plant (2013 to 2021)
  - Solar field inlet, outlet temperature
  - Inlet mass flow
  - Thermal outlet power
  - Average focus of solar field
  - Effective irradiance
  - Time of day and time of year
- Difference to deterministic model YACOP
- Scaled with mean and std. deviation
- Sliding window dataset with 5 consecutive days
- Split into train, validation and test dataset





Methods
Learning representations from raw time series data

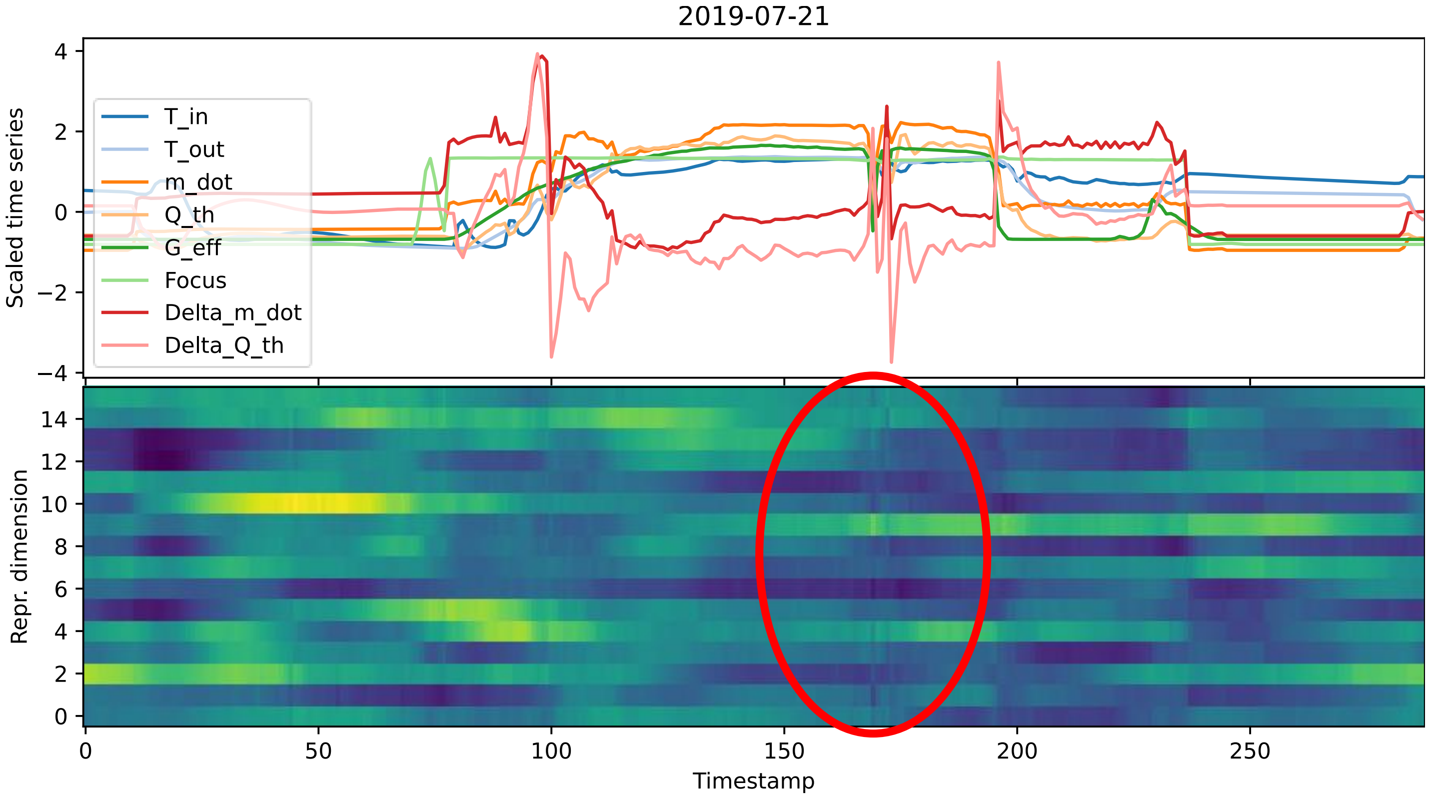
- Representations capture the essential structure of time series data, without the need for data labels
- TS2Vec model [2]
  - Self-supervised
  - Contrastive learning
  - Flexible representations (e.g. for each time step, or entire sample)
  - Fast training even with large dataset (years of data)



from Yue et al. 2021 [2]

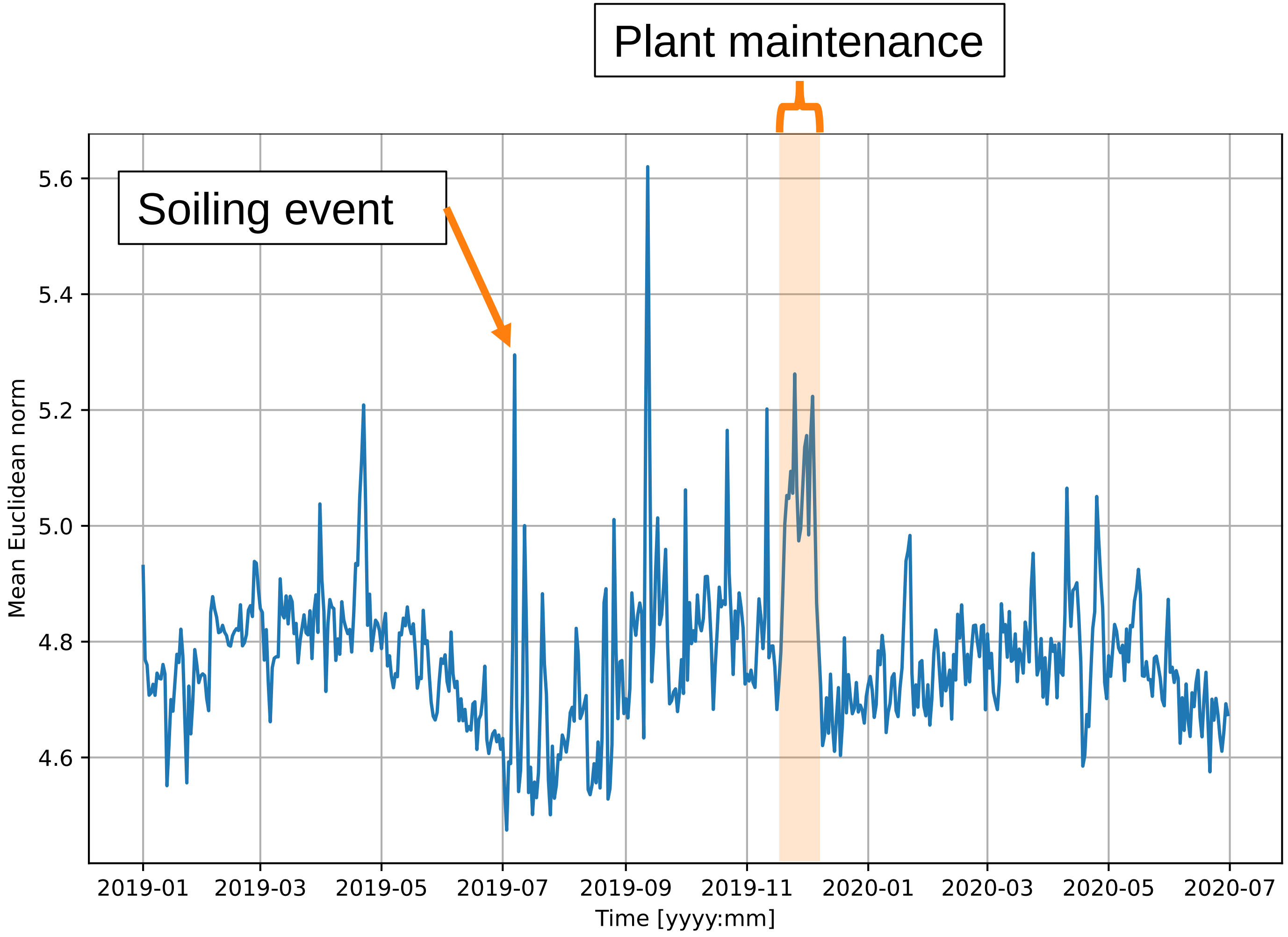
Results
Visualization of learned representations

- Selection of representations with max. variance
- Start-up and cool-down are visible in the representations
- Interruptions in the irradiance are visible as well
- **The major benefit of the representations comes from other downstream tasks**
  - Anomaly detection
  - Classification
  - Input for other models



Results
Application: Representations used for anomaly detection

- Similarity between different representations can be measured with the Euclidean norm
  - $EN(x_{d,t}) = \sqrt{\sum_{i=1}^{n}(x_{d,t,f})^2}$
  - Similar operation days → similar representations → similar Euclidean norms
- High peaks in the Euclidean norm correspond to unusual evens
  - Soiling event with high dust loads
  - Plant maintenance
- **High potential for an anomaly detection use-case**

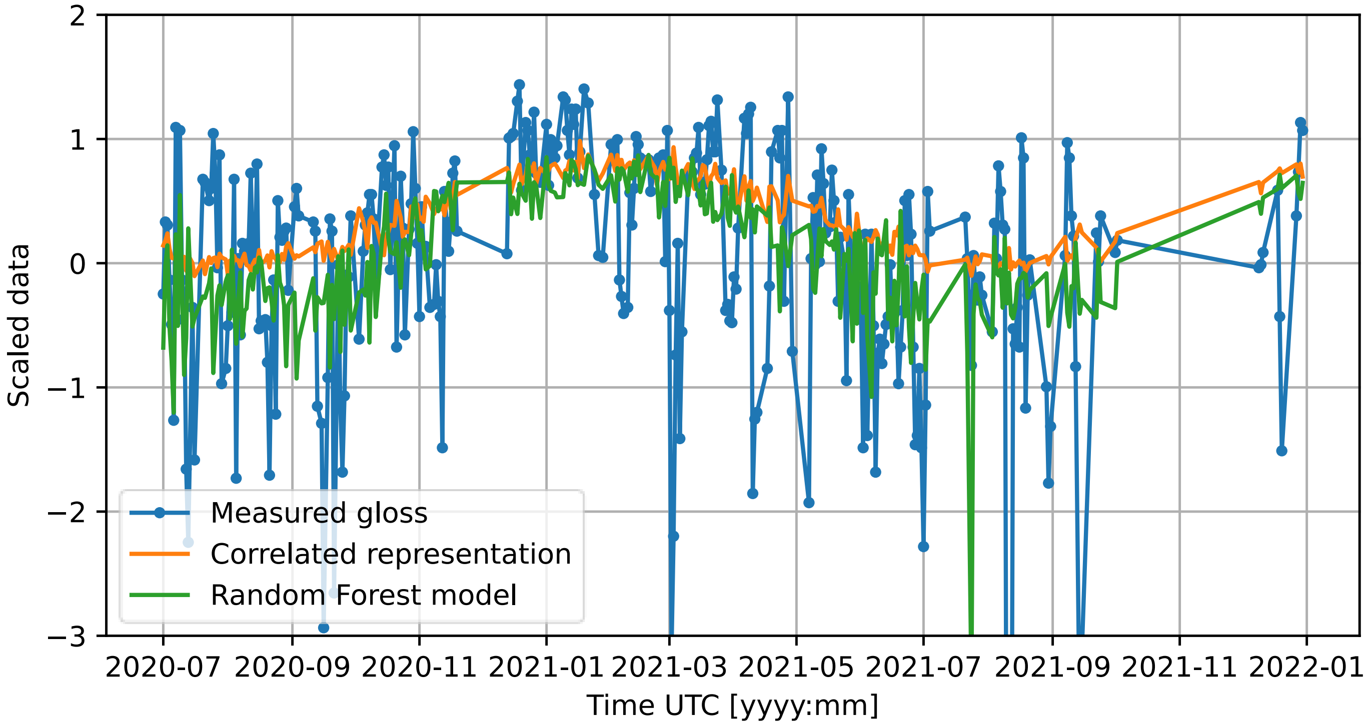


Results

Application: Representations compared to soiling values

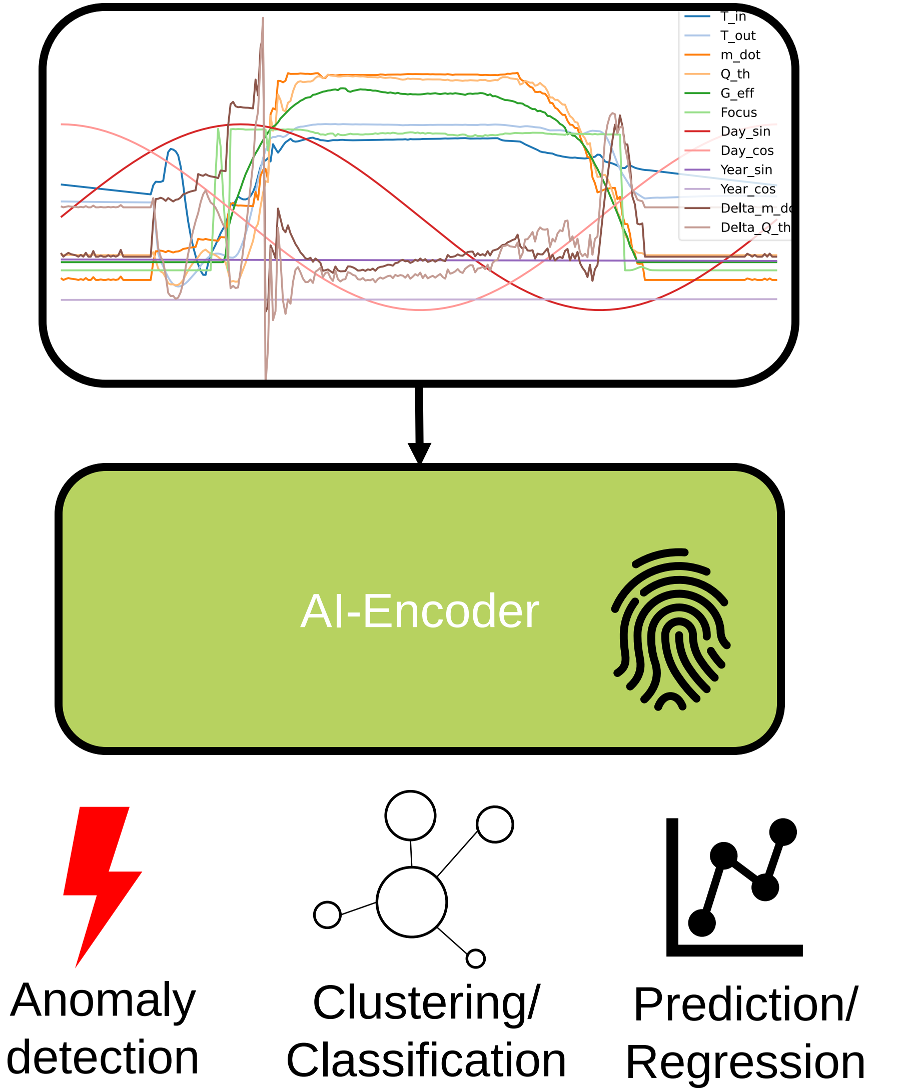
- Gloss values are taken in the Andasol 3 plant as measure for soiling
- High seasonality of soiling is covered by the representations
- A simple Random Forest model using the five most correlated representations further improves the prediction

[3]



Conclusions

- Model-based condition monitoring does not require additional hardware installation
- Extracting the solar field condition is one example of the capabilities of data-driven modeling approaches
- Downstream tasks can benefit from the representations of the pre-processing step
- Paves the way for other data-driven models
  - Anomaly detection
  - Time series classification/clustering
  - Prediction models



More project results will be presented in the ATA Insights webinar **“Digital solutions for monitoring and optimizing CSP and PV plants”** on Wednesday, **November 19, 3–5 p.m. CET**

THANK YOU FOR YOUR ATTENTION

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Federal Ministry
for the Environment, Climate Action,
Nature Conservation and Nuclear Safety

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References

[1] Loevenich et al., YACOP - A Fully Flexible Modeling Environment for the Techno-Economic Assessment of Energy Systems. Kölner Sonnenkolloquium 2024, 2024-06-26, Jülich, Deutschland. https://elib.dlr.de/206463/

[2] Yue et al., TS2Vec: Towards Universal Representation of Time Series, AAAI 2021. http://arxiv.org/pdf/2106.10466v4

[3] Gloss measurement with Zehntner ZGM 1110, Source Zehntner GmbH

[4] https://noorenergy.ae/parabolic-trough/