Optimization of Cleaning Strategies Based on ANN Algorithms Assessing the Benefit of Soiling Rate Forecasts

German Aerospace Center (DLR), Plataforma Solar de Almería, Spain

Felix Terhag, **Fabian Wolfertstetter**, Stefan Wilbert, Oliver Schaudt, Tobias Hirsch

fabian.wolfertstetter@dlr.de

+34 950611877

DLR

Outline

- Introduction
- Soiling related measurements
- Solar field model and comparison parameter
- Reinforced learning algorithms
- Creation of synthetic data series
- Performance of ANN strategies

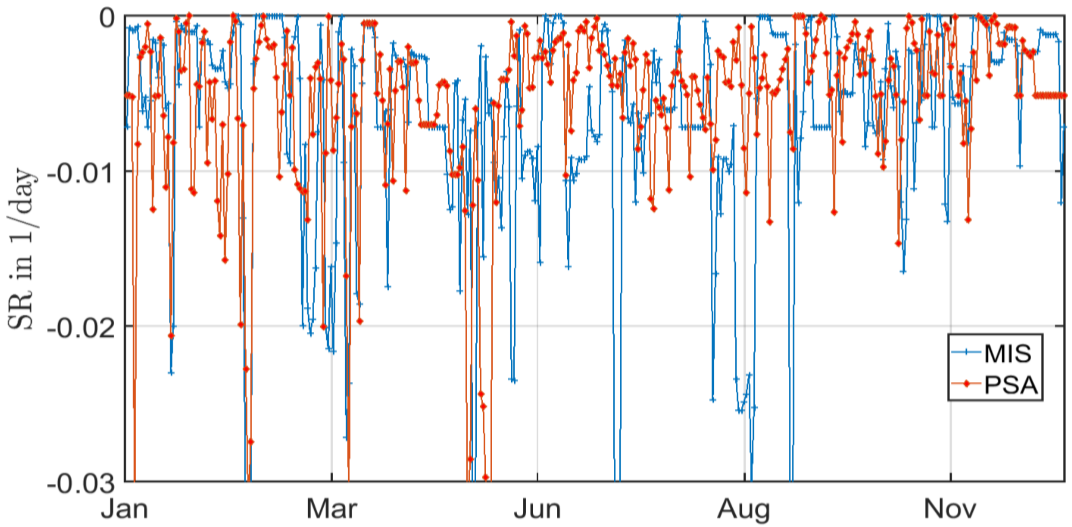
Cleaning and soiling

- Cleaning operators have to find the best trade-off between reduced **cleaning costs** and increased optical **solar field efficiency**
- Cleaning performance has to be quantified **financially**
- **Time resolved** analysis and **realistic soiling** rate dataset is crucial

Soiled trough at PSA

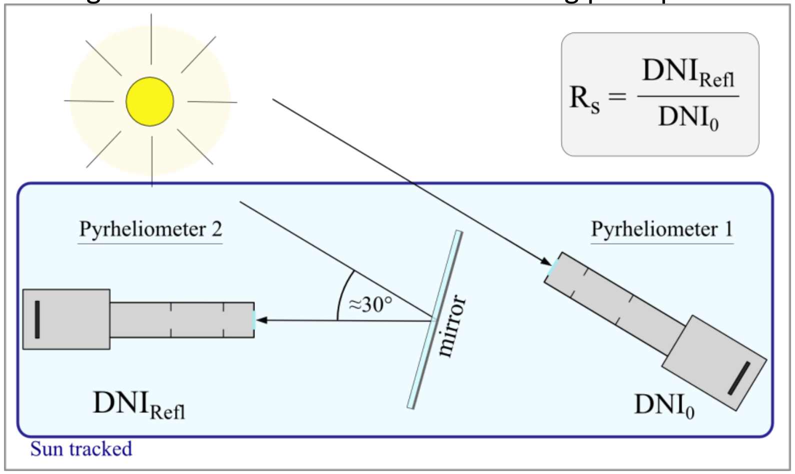
Soiling measurement

- TraCS instrument measures
  Cleanliness = $\rho_{soiled} / \rho_{clean}$
- **5 years** of soiling rate data at PSA
- >**28 years** of irradiance and weather data for yield calculations



Soiling rate data from PSA and Missour, Morocco 2016

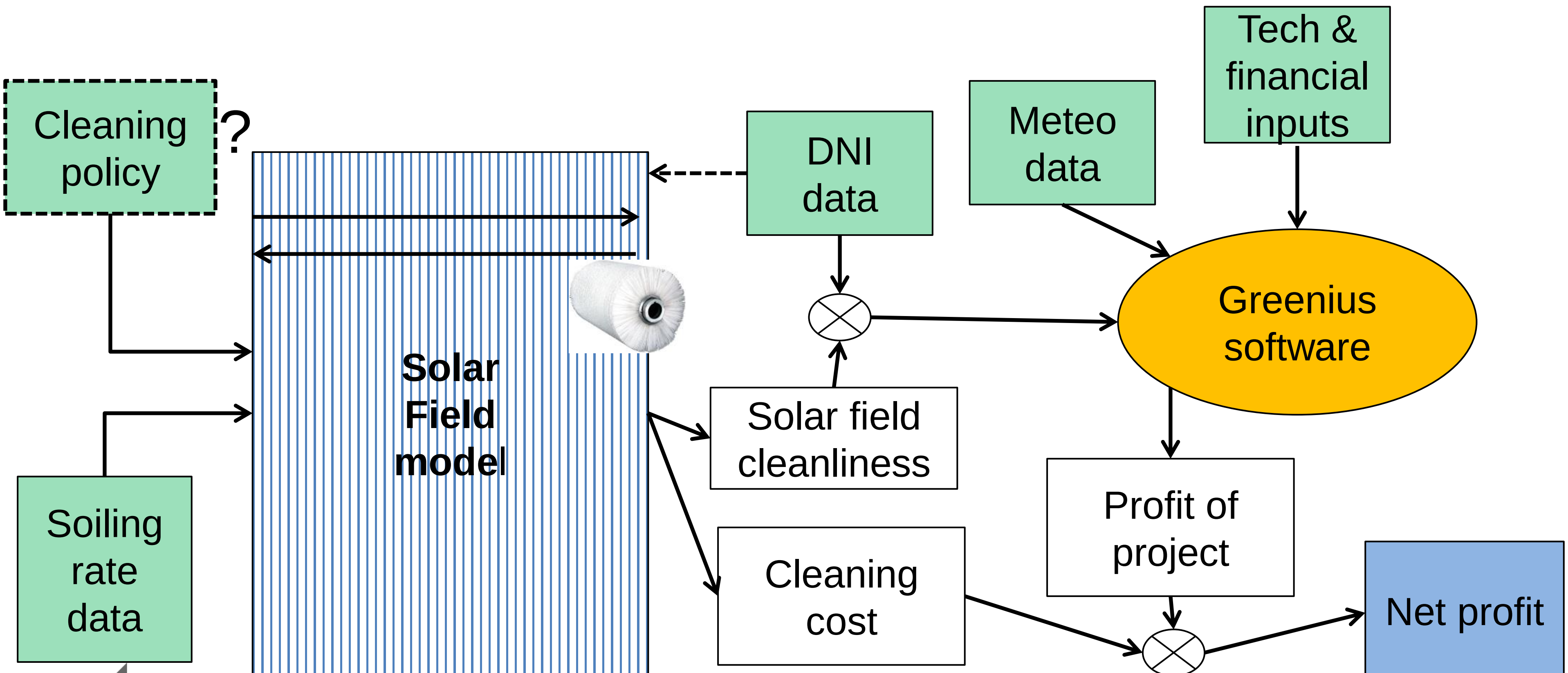
Tracking **C**leanliness **S**ensor – TraCS - working principle



Wolfertstetter, F., Pottler, K., Alami, A., Mezrhab, A., & Pitz-Paal, R. (2012). A novel method for automatic real-time monitoring of mirror soiling rates. SolarPACES 2012.
Wolfertstetter, F.: *Effects of soiling on concentrating solar power plants*. PhD thesis, Technische Hochschule (RWTH) Aachen, 2016

Cleaning optimization: solar field model

- Solar field model tracks cleaning vehicles and each troughs cleanliness
- Assumption: all troughs soil with same soiling rate
- Output: net profit = project‘s profit – cleaning cost



Cleaning optimization: technical and financial inputs

- 50 MW plant with 7.5 h storage
- Water and brush based cleaning vehicles
- Collect cleaning related technical and financial parameters
- Cleaning costs:
    - Labor, water, fuel, depreciation of cleaning vehicles

COURTESY OF ABENGOA

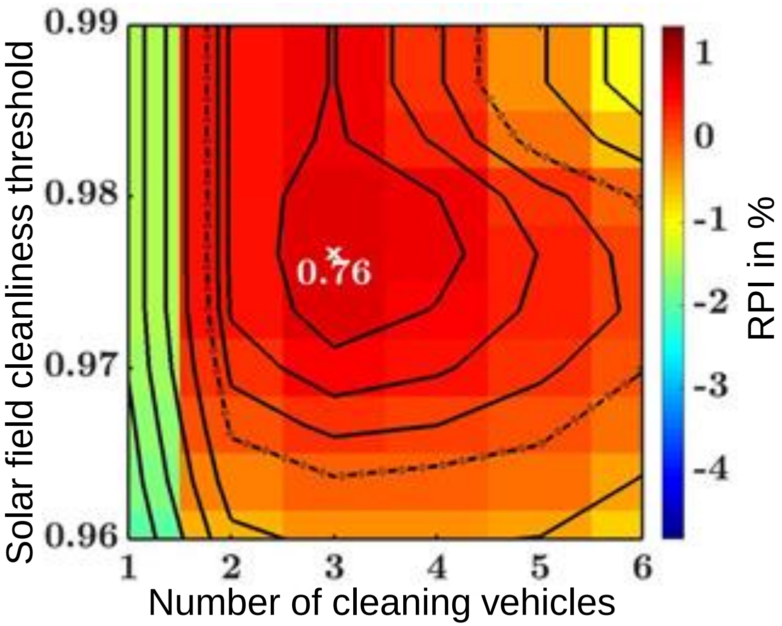
Parameter	Value
Nominal turbine power	$49,9 MW$
Number of loops in Solar Field	156
Aperture area of solar field	510.000 m^2
Thermal storage	7.5 h
Cooling	water
Planned lifetime	25 years
DNI-yearly sum at PSA	2388 $kWh/m^2/a$
Equity ratio	30 %
Specific operating costs	1.8 $EUR/m^2/a$
Feed-in tariff	0.27 EUR/kWh
Cleaning velocity for one unit	9 loops / shift
Number of personnel per vehicle	1
Cleaning vehicle fuel consumption	6 – 8 l/loop
Cleanliness after cleaning	0.986
Demin. water consumption of cleaning unit	1 m^3/loop
Estimated lifetime of cleaning unit	15 years

DLR

Wolfertstetter, F., Wilbert, S., Dersch, J., Dieckmann, S., Pitz-Paal, R., & Ghennioui, A. (2018). Integration of Soiling-Rate Measurements and Cleaning Strategies in Yield Analysis of Parabolic Trough Plants. *Journal of Solar Energy Engineering*, *140*(4), 041008.

Cleaning optimization: policy comparison

- A **reference cleaning strategy** is chosen as a reference point: constant, daily cleaning in one shift with 1 vehicle
- Cleaning policies are compared to reference by **relative profit increase (RPI)**
- **Previous study**: condition based cleaning policies:
  - Vary number of vehicles and cleanliness threshold

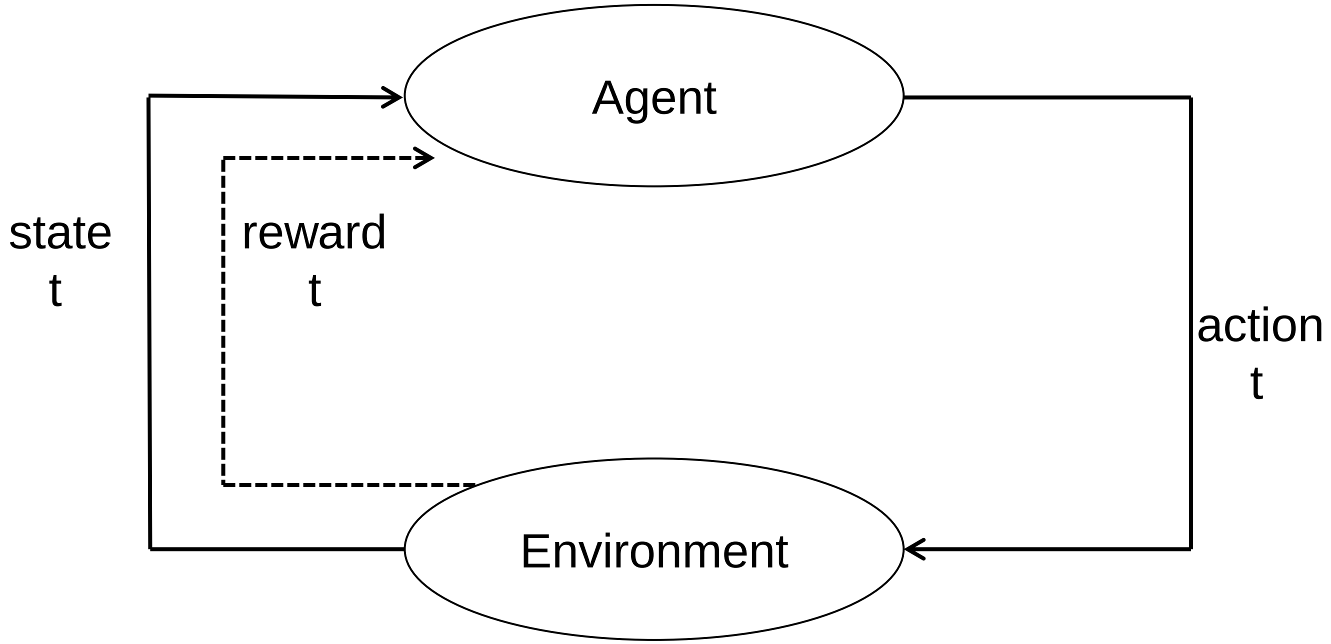


Can cleaning strategy be improved by reinforced Learning and forecast?

Wolfertstetter, F., Wilbert, S., Dersch, J., Dieckmann, S., Pitz-Paal, R., & Ghennioui, A. (2018). Integration of Soiling-Rate Measurements and Cleaning Strategies in Yield Analysis of Parabolic Trough Plants. *Journal of Solar Energy Engineering*, *140*(4), 041008.

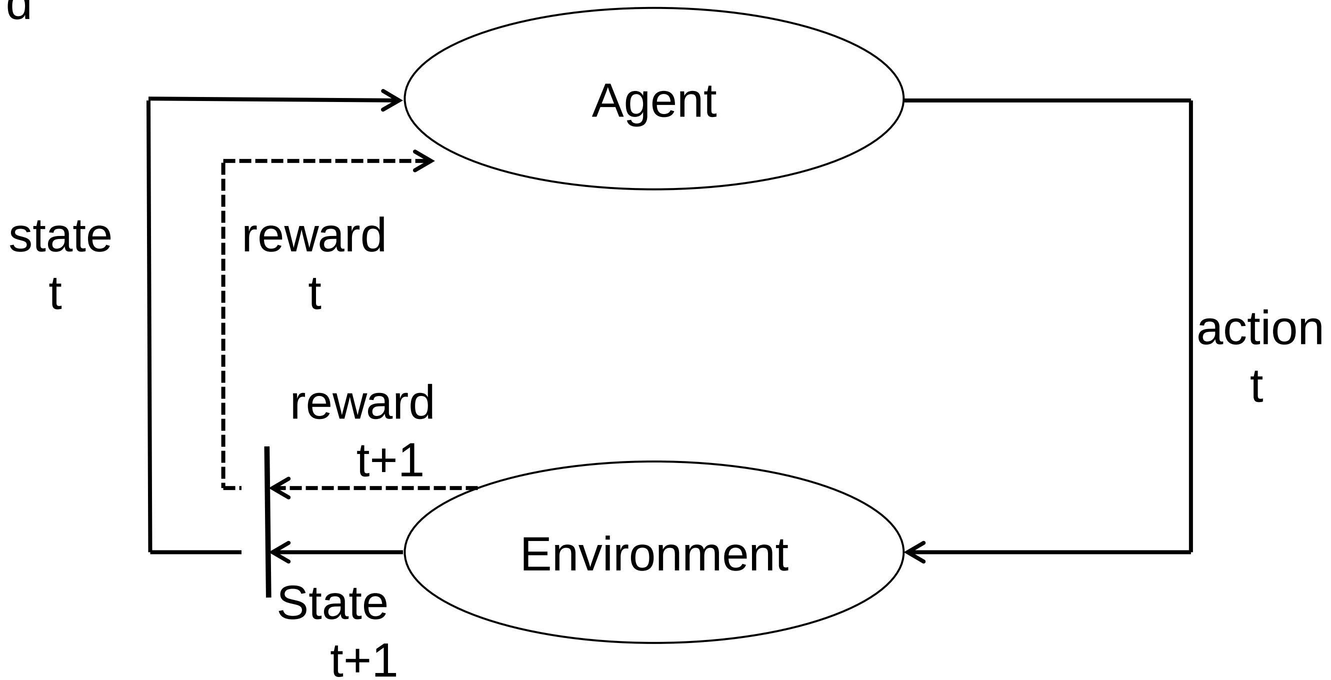
Artificial Neural Networks: Reinforced learning

- Agent takes action depending on the environment



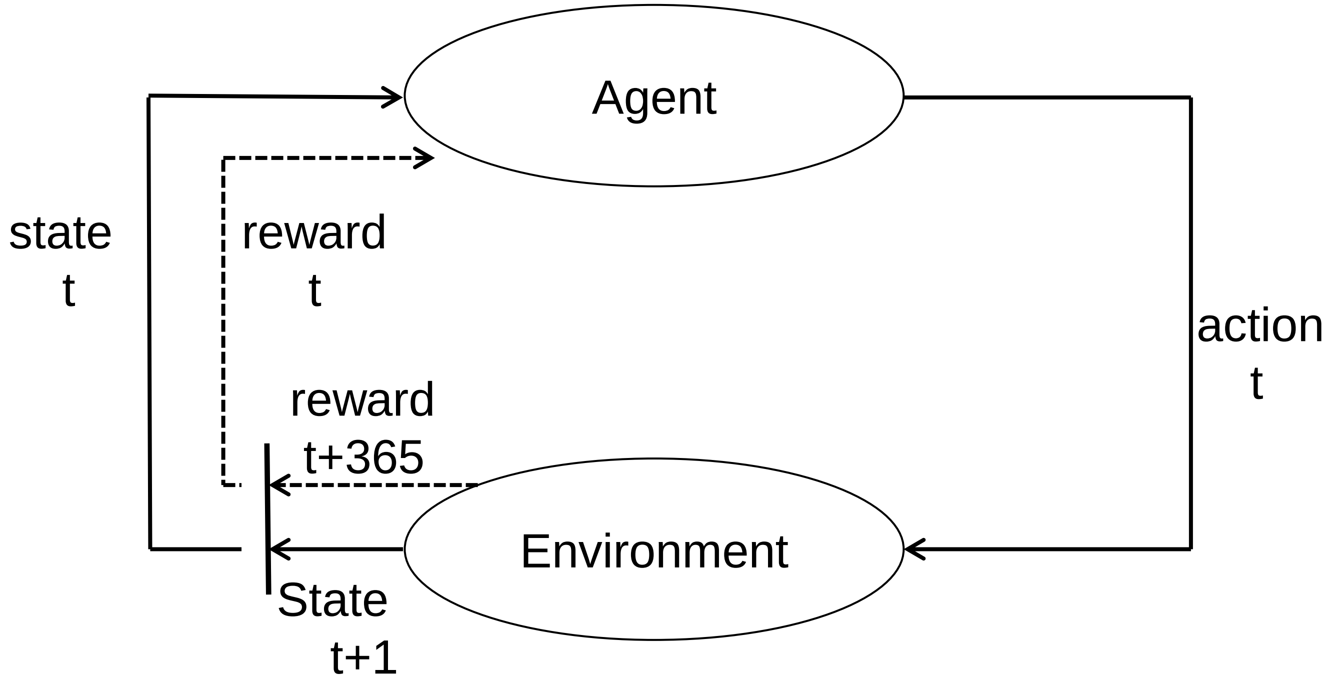
Artificial Neural Networks: Reinforced learning

- Agent takes action depending on the environment
- Actions influence environment and creates a reward feedback
- **Learning process**: Agent is updated after each run => negative or positive feedback on current policy according to reward
- The fully trained agent can be applied to any new environment to deliver high reward



Artificial Neural Networks: Reinforced learning

- agent = cleaning policy
- action = daily cleaning decision
    - Clean with 0 – 2 vehicles in 1 or 2 shifts each
- state = solar field cleanliness, weather data, optional: **forecast** for irradiance class and high/low soiling rate
- Reward = RPI



Reinforced Learning: Reward and training

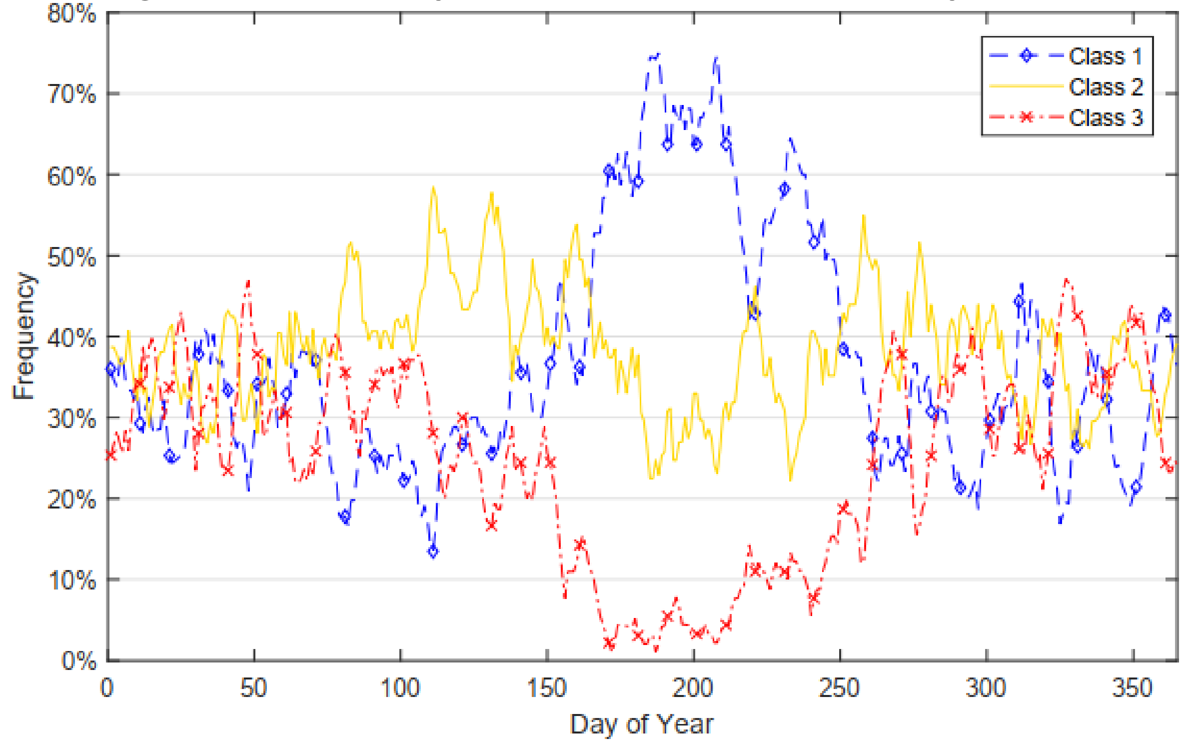
- Each training run involves full simulation year, i.e. 365 states and cleaning decisions
- Option to provide agent with soiling rate and weather forecast information
- Training of reinforced learning agent requires a **large amount of data**
- 5 years of soiling data and 28 years of weather data is **not enough** for reinforced learning

=> need to increase database by **synthetic data extension**

Synthetic data extension: weather

- Measurement days are classified for **DNI variability** (clear sky, intermittent, cloudy) [1]
- **Transition probabilities** are determined
- Original measurement days are drawn from a 14 day time window according to transition probabilities
- >5,000 data years are created

Average DNI variability class distribution over 28 years at PSA

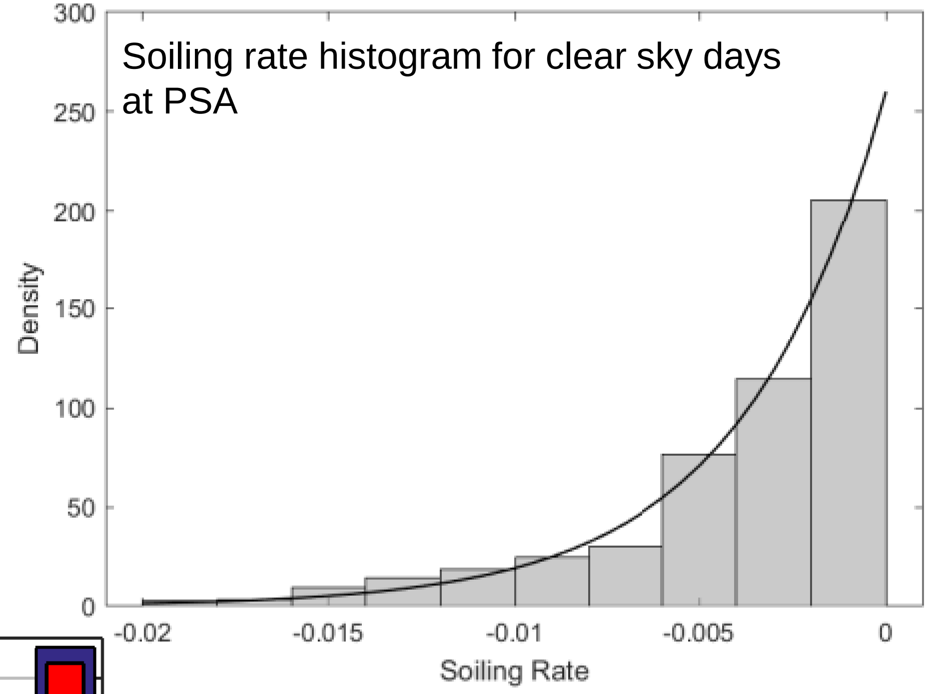


Current day \ Following day	Class 1	Class 2	Class 3
Class 1	58 %	32 %	10 %
Class 2	31 %	45 %	24 %
Class 3	17 %	38 %	45 %

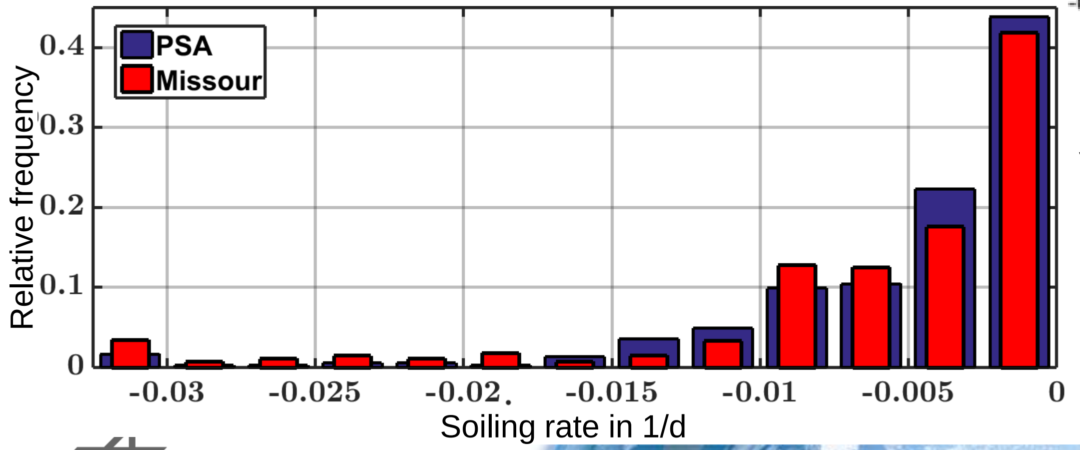
1 M. Schroedter-Homscheidt, M. Kosmale, S. Jung, and J. Kleissl, “Classifying ground-measured 1 minute temporal variability within hourly intervals for direct normal irradiances,” *Meteorologische Zeitschrift*, 2018.

Synthetic data extension: soiling rate and natural cleaning

- Soiling rate is drawn according to probability for each variability class
- Rain cleaning action quantified in cleaning efficiency: how much of the existing dirt is removed by rain



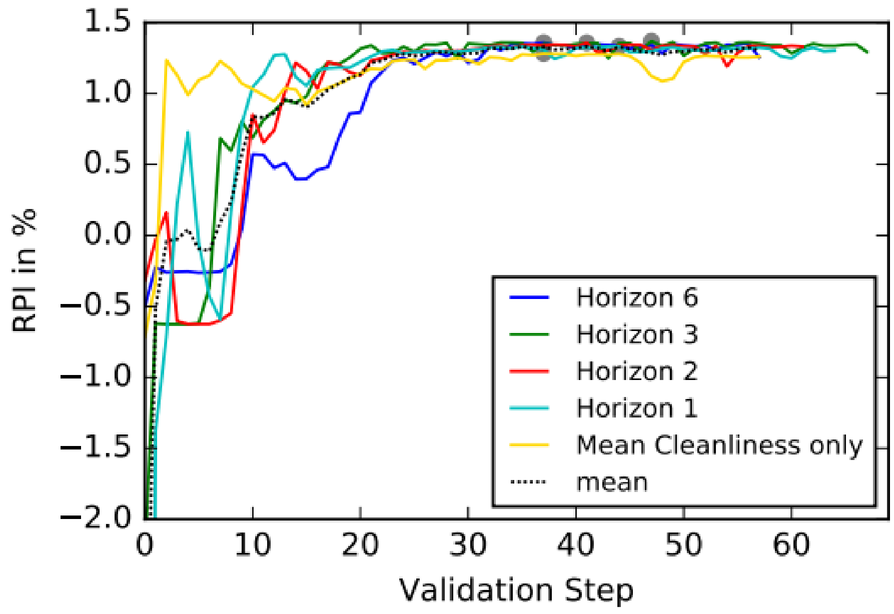
Soiling rate histogram for clear sky days at PSA

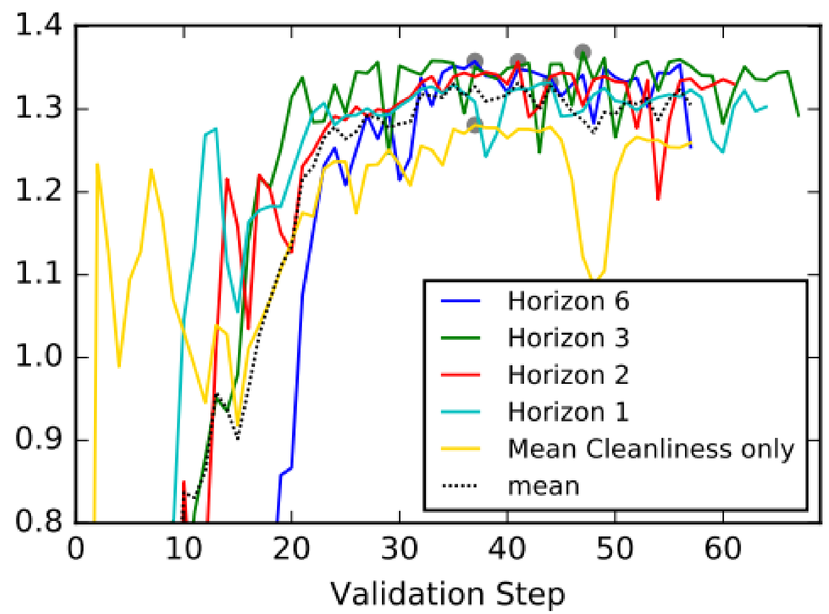


Soiling rate histograms for PSA and Missour, Morocco and all classes

Learning progress

- Agent begins with **random strategy**
- **Agent is updated** after each training year according to reward
- Repeat 10 times on each test year and 15 different years (**training run**)
- **Validation set**: fix dataset of 20 years
- **Agent is tested** on validation set after each training run
- RPI increases with training run
- **Exit condition**: no RPI-improvement in the last 20 training runs
- Resulting agent is the final cleaning policy





Application of soiling forecast in cleaning policy: results

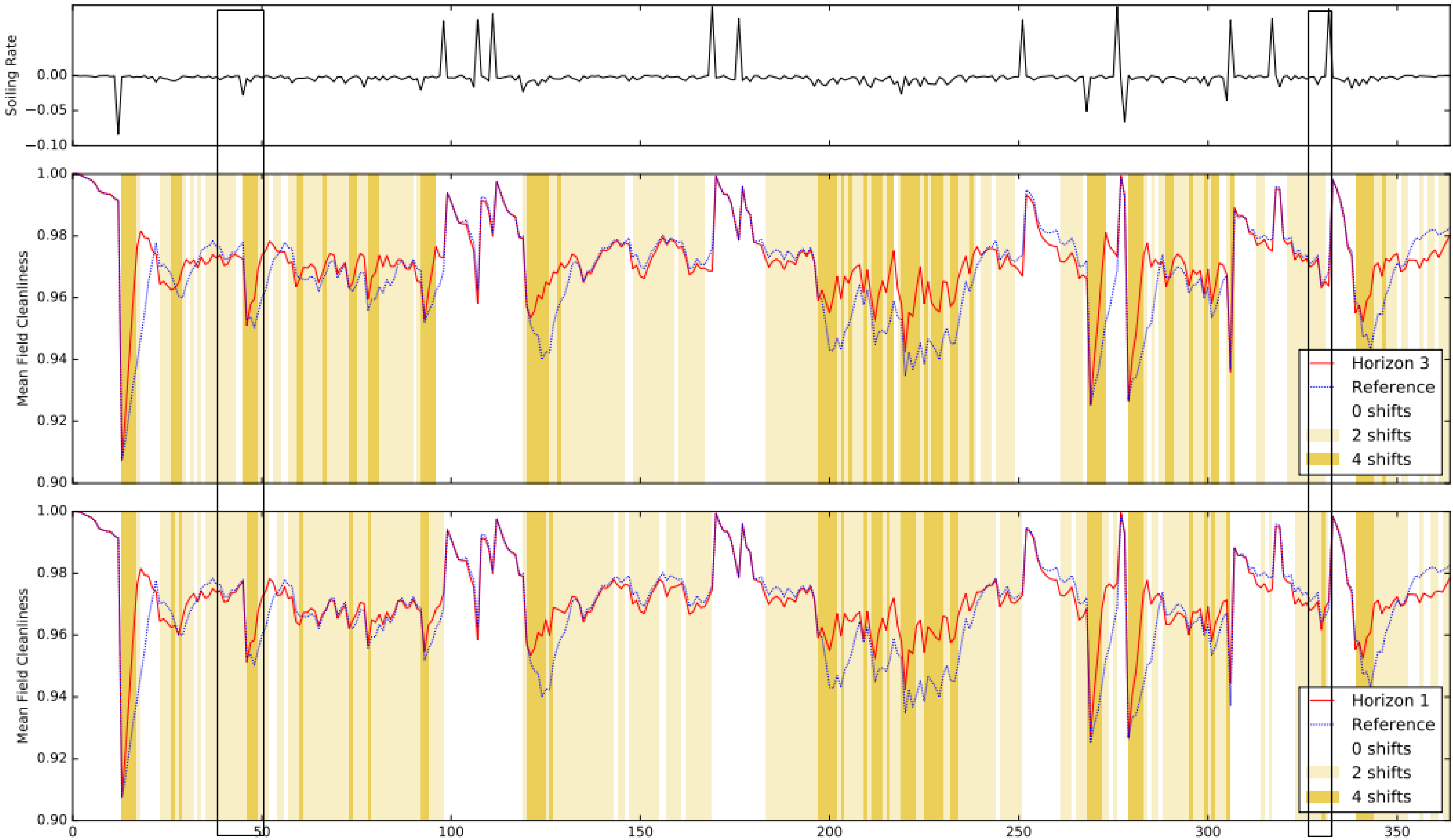
- Reinforcement learning strategy nearly doubles the RPI of the condition based strategy if no forecast is provided
- Reinforcement learning strategies achieve RPI of 1.3 % if no forecast is provided
- RPI of 1.4% with forecast information

- Note: PSA is not a heavy soiling location
- Much higher results are expected for regions with higher dust loads

Forecast Horizon in days	RPI in [%]
ø	1.28
1	1.33
2	1.36
3	1.37
6	1.36

DLR

Evolution of soiling and cleaning in solar field



Wolfertstetter, F., Wilbert, S., Dersch, J., Dieckmann, S., Pitz-Paal, R., & Ghennioui, A. (2018). Integration of Soiling-Rate Measurements and Cleaning Strategies in Yield Analysis of Parabolic Trough Plants. *Journal of Solar Energy Engineering*, *140*(4), 041008.

Conclusion

- Solar field model developed: add on to yield analysis software such as greenius
- Data extension algorithm developed for training of reinforcement learning algorithms
- Reinforcement learning applied to cleaning optimization
- Reinforcement learning agent nearly doubles the profit increase compared to condition based cleaning strategies
- Inclusion of forecast for high/low soiling rate and irradiance class can further increase the profit
- Better results expected for sites with higher soiling load

Thank you for your attention

fabian.wolfertstetter@dlr.de

Recommended literature on soiling model:

http://wascop.eu/wp-content/uploads/2018/06/WASCOP_deliverable_3.2_final_plainText.pdf

Upcoming talks at solarPACES:
Thursday, 13:45 water consumption management session : cleaning strategy optimization
Friday 08:50 solar resource assessment: soiling model