Optimized Cleaning Strategies for CSP

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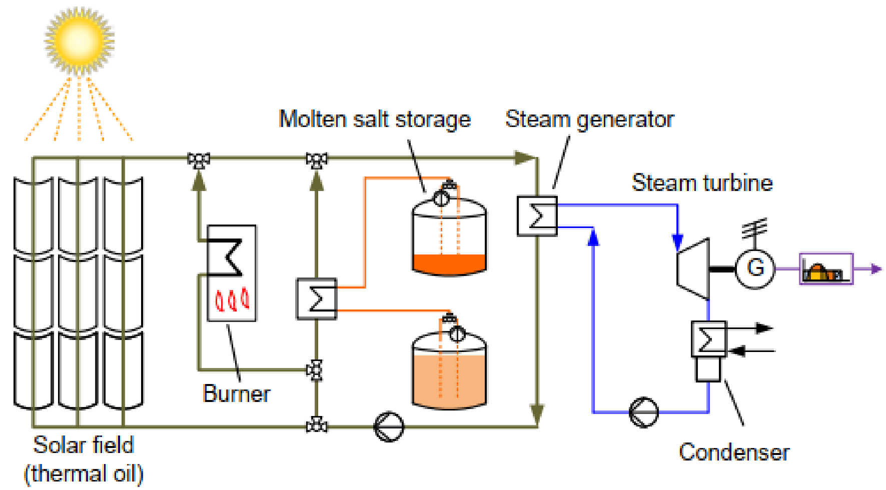
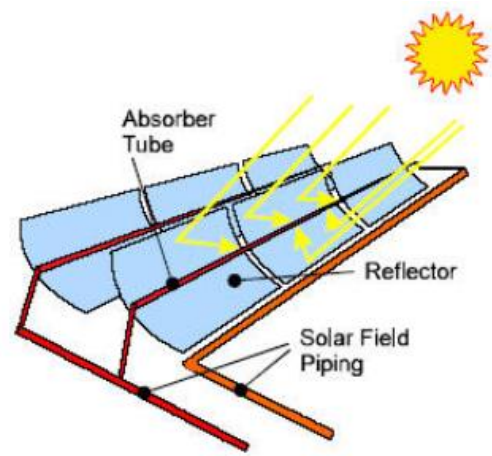
Outline

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

Concentrating Solar Power



- Concentration of direct sunlight with mirrors to achieve high temperatures
- Provision of electricity (turbine cycle), process heat, desalination
- CSP uses only **direct component** of solar irradiation (=> soiling impact higher as in PV)
- Cost effective **thermal storage** option
- **Grid stabilizing** effect thanks to turbine



Images property of: Torresol energy, MASEN, SolarPACES, [T]

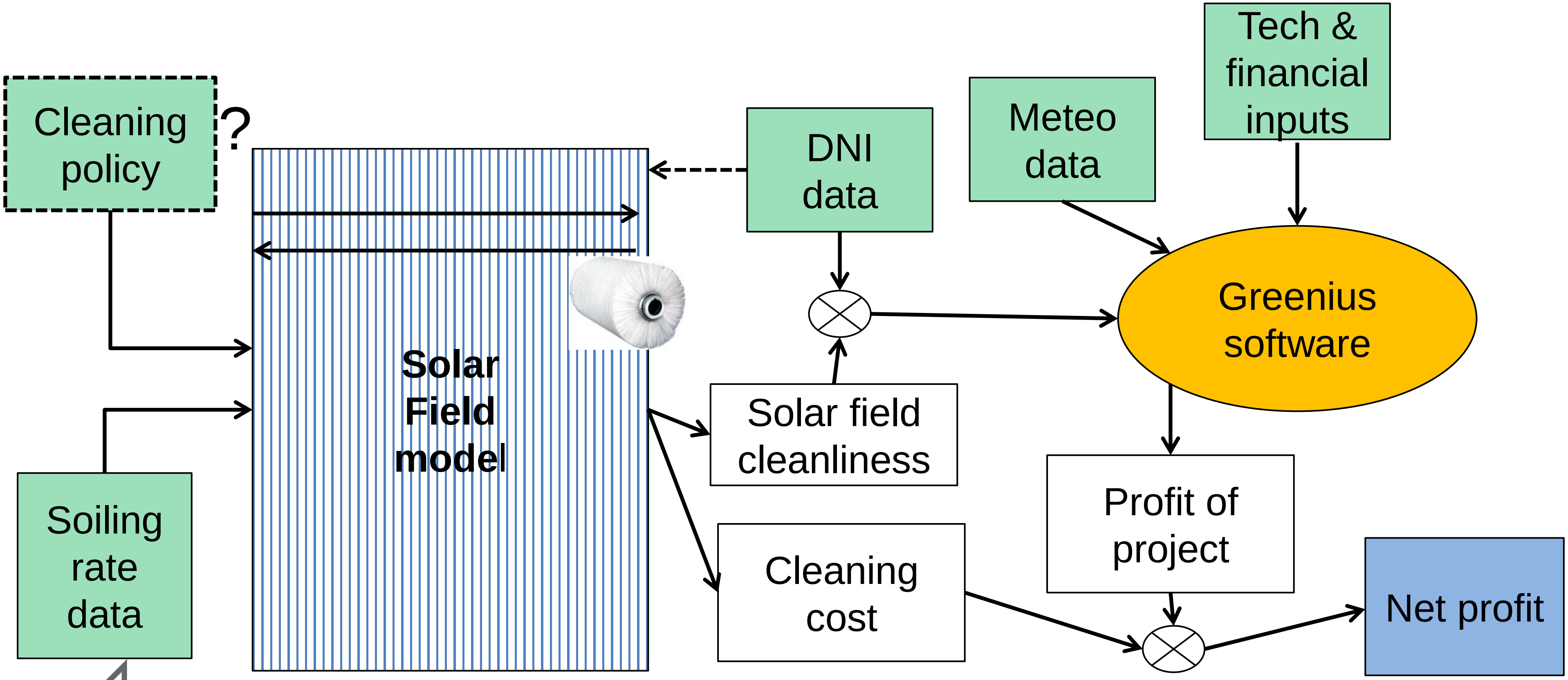
Cleaning and soiling

- 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

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: scenario & inputs

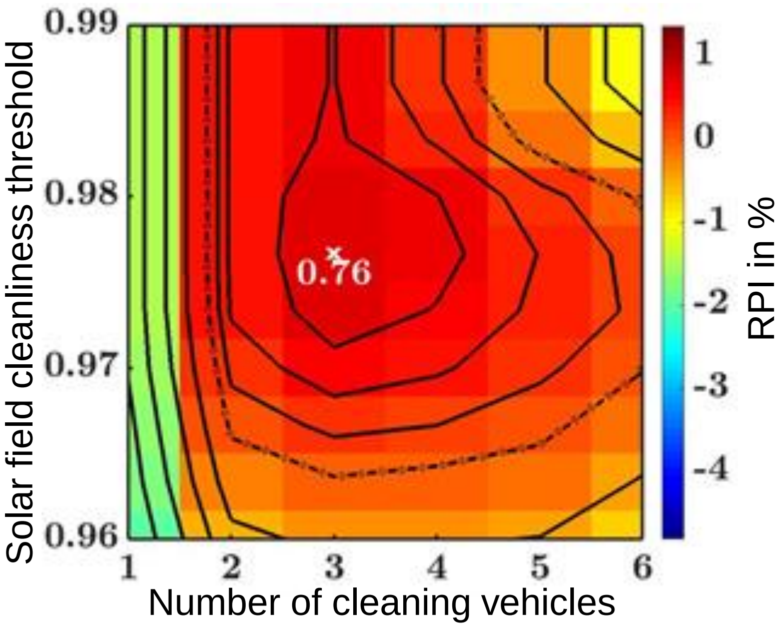
- 50 MW plant with 7.5 h storage
- Water and brush based cleaning vehicles
- Cleaning related technical and financial parameters (see table)
- Cleaning costs:
    - Labor, water, fuel, depreciation of cleaning vehicles
- **5 years** of soiling rate measurement data at PSA
- >**28 years** of irradiance and weather data

Parameter	Value
Nominal turbine power	$49,9MW$
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

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

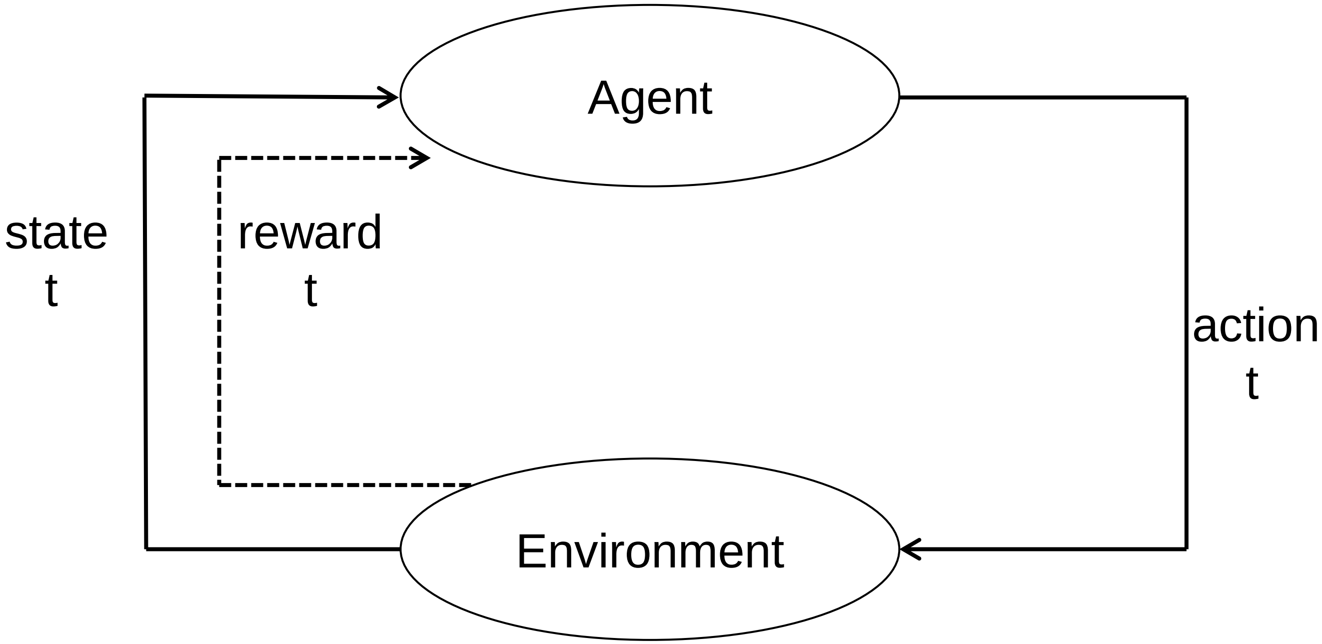


Can cleaning strategy be improved by reinforced Learning and forecast?

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.

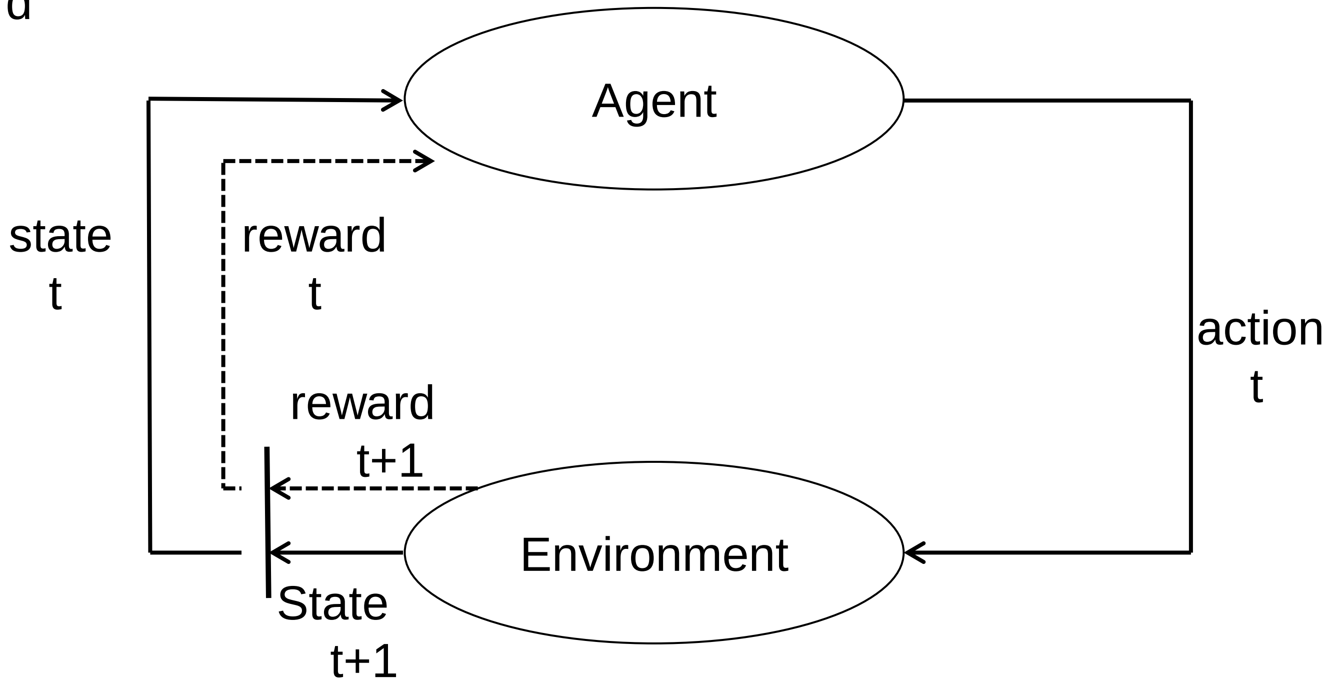
Artificial Neural Networks: Reinforced learning

- Agent takes action depending on the environment



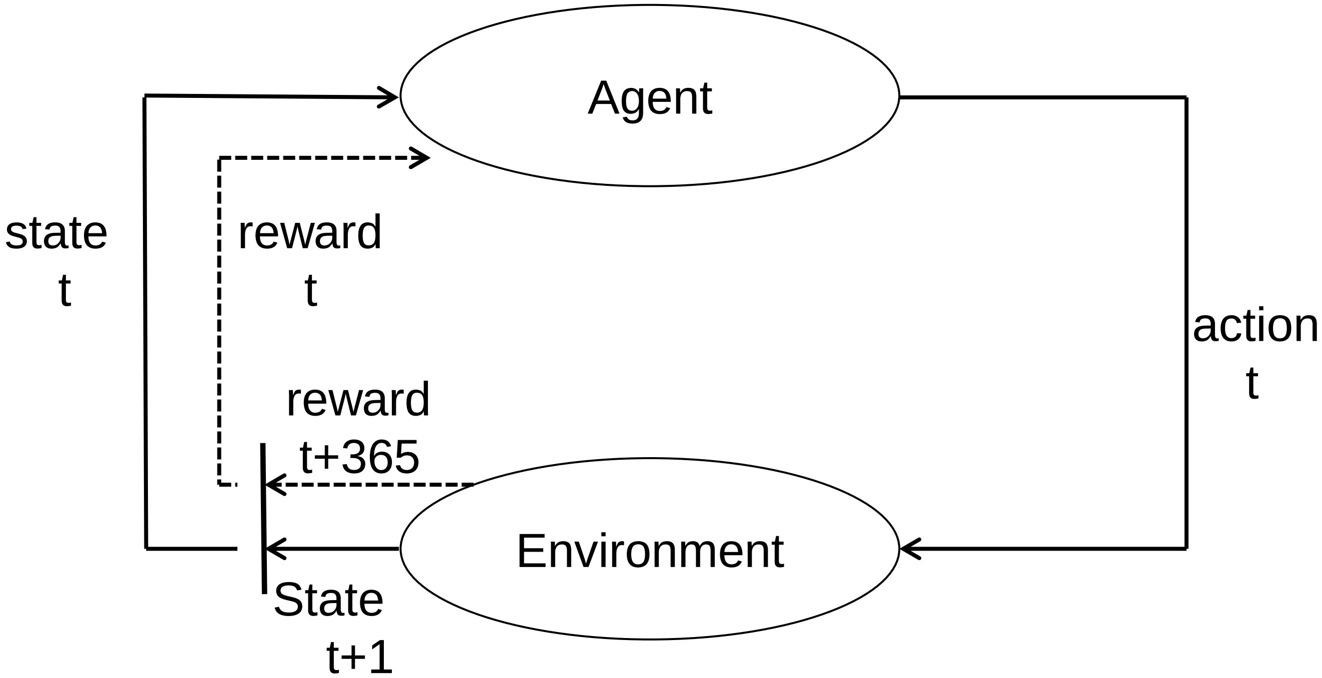
Artificial Neural Networks: Reinforced learning

- 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

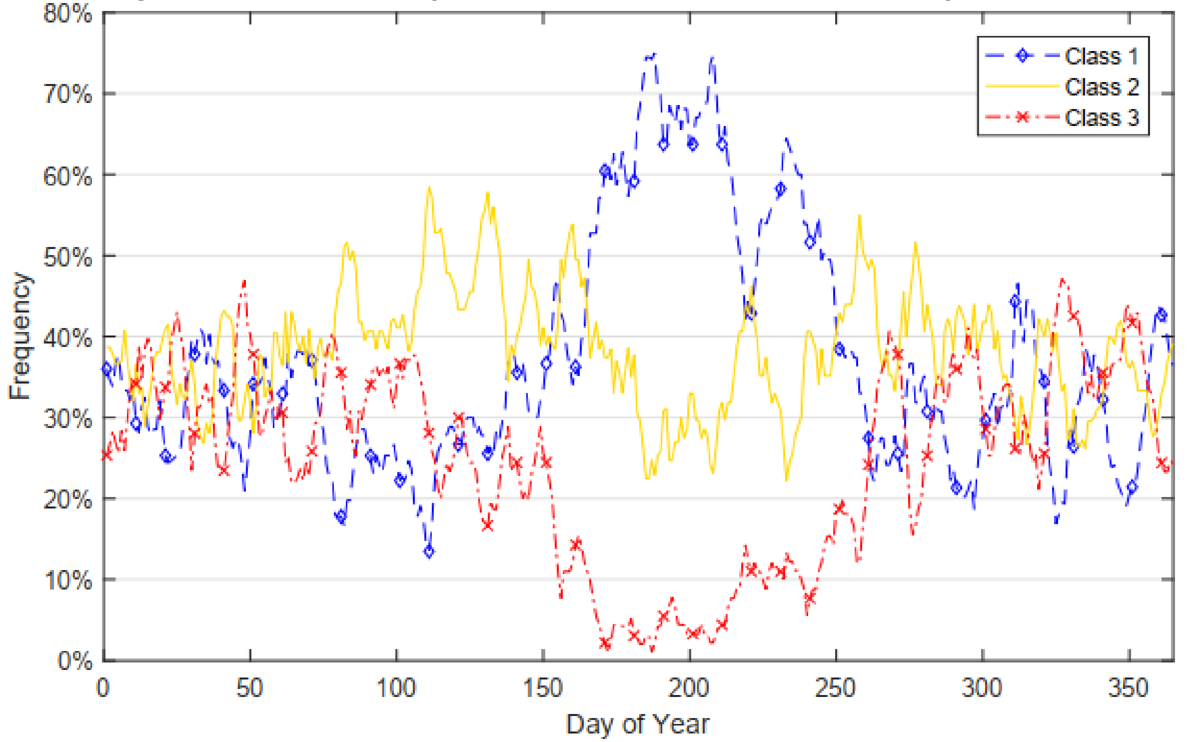
- Each training run involves full simulation year, i.e. 365 states and cleaning decisions
- Option to provide agent with soiling rate and weather forecast information
- Training of reinforced learning agent requires a **large amount of data**
- 5 years of soiling data and 28 years of weather data is **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

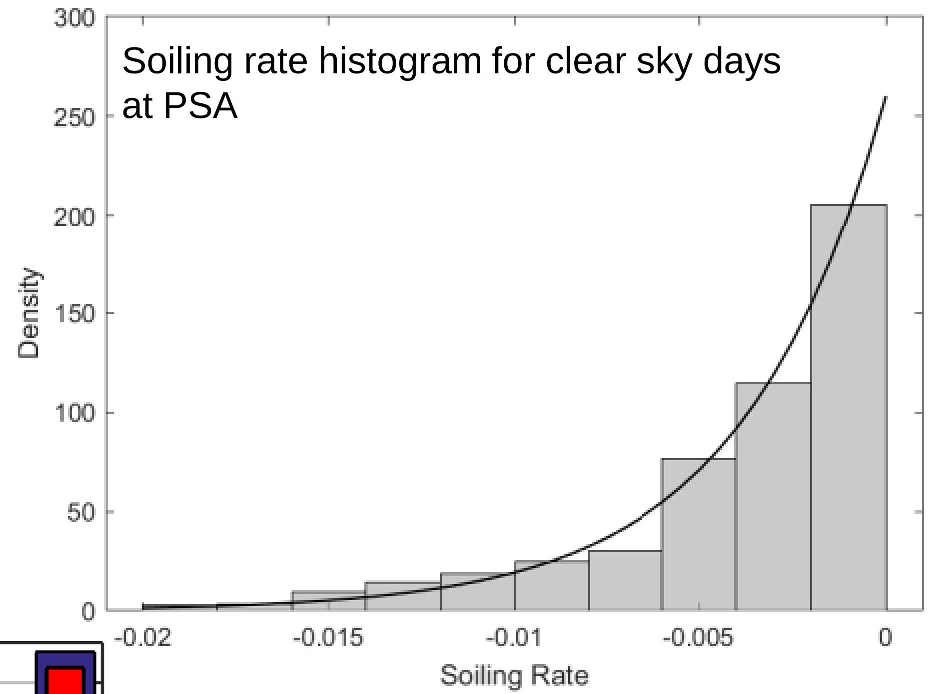


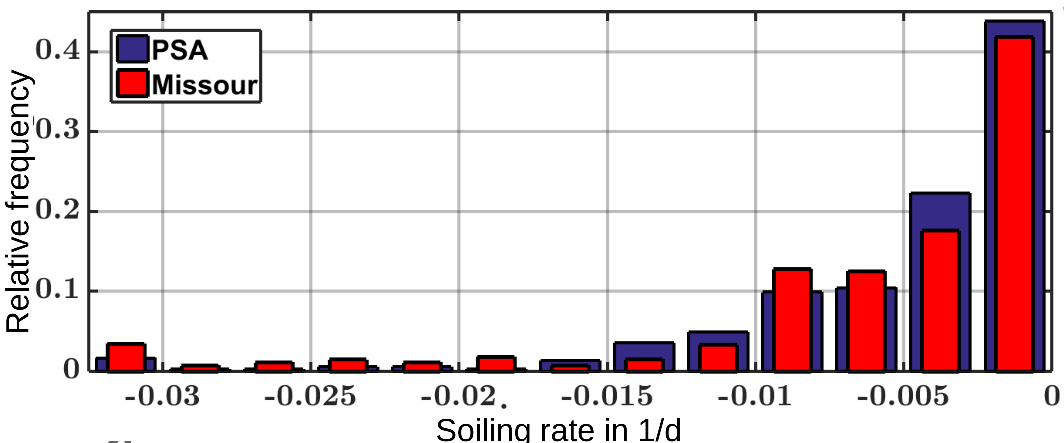
Current day \ Following day	Class 1	Class 2	Class 3
Class 1	58 %	32 %	10 %
Class 2	31 %	45 %	24 %
Class 3	17 %	38 %	45 %

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

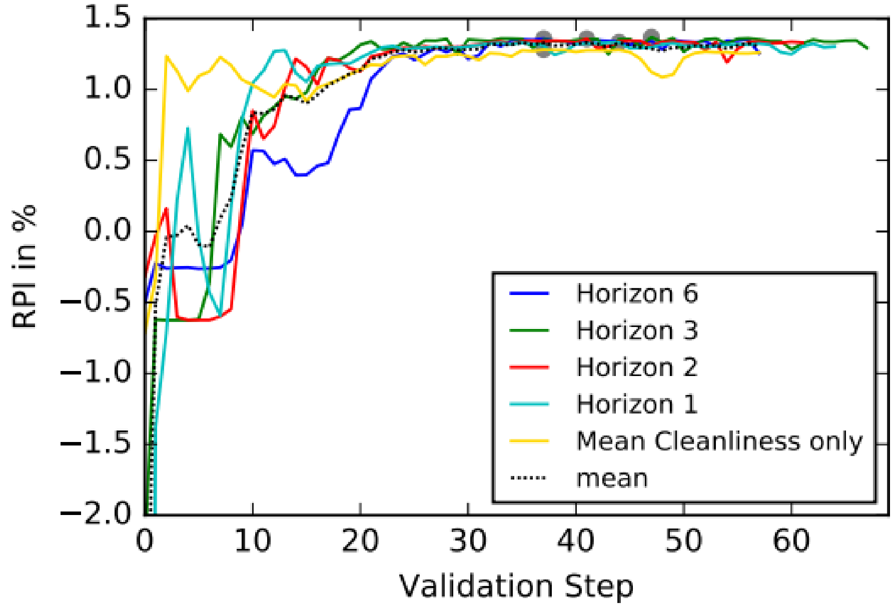


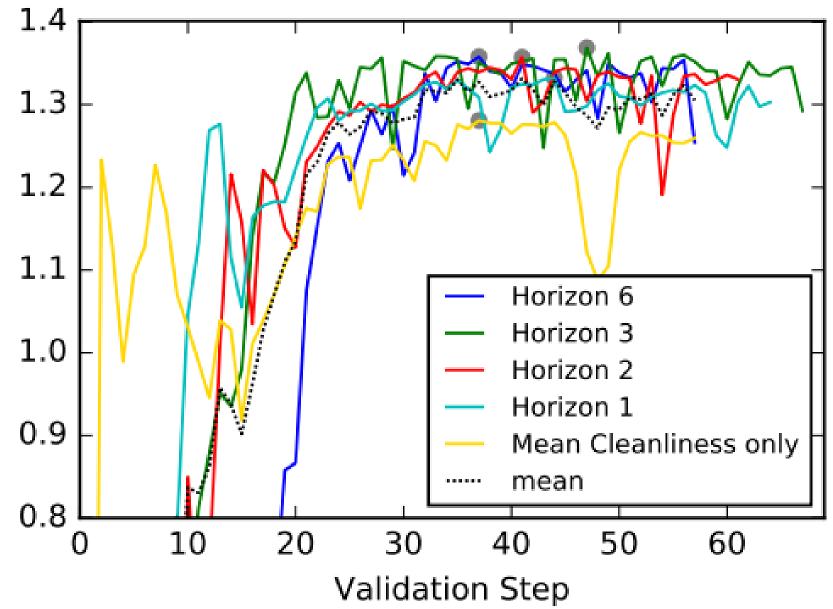


Soiling rate histograms for PSA and Missour, Morocco and all classes

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





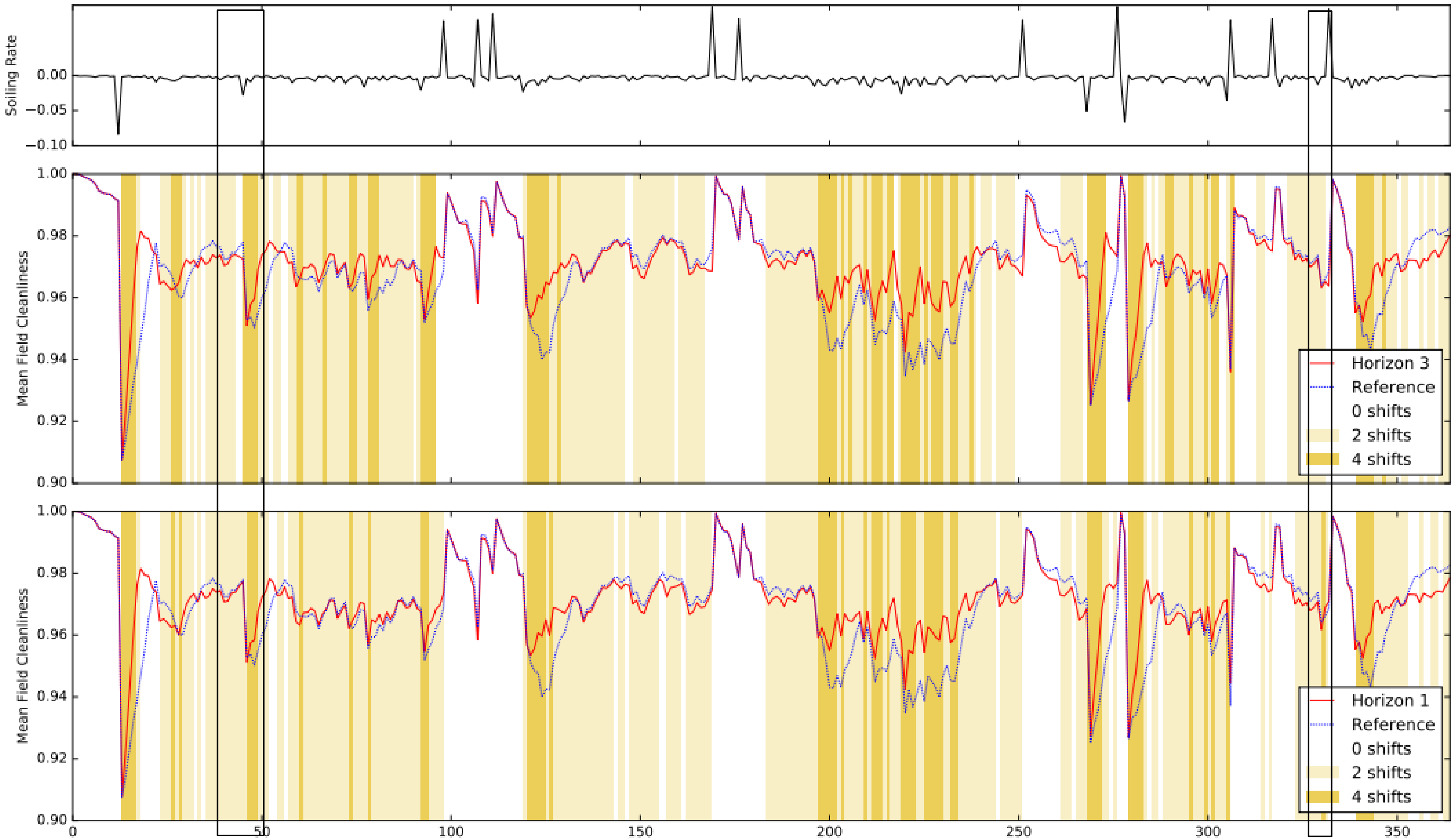
Application of soiling forecast in cleaning policy: results

- 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

Evolution of soiling and cleaning in solar field



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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

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Recommended literature on soiling model:
http://wascop.eu/wp-content/uploads/2018/06/WASCOP_deliverable_3.2_final_plainText.pdf

Soiling rate

- Soiling rate = reduction of cleanliness over time
- Soiling rate is dependent on time and location
- Not (yet) a standard measurement parameter
- Little information available in target regions for so