

# Optimized Cleaning Strategies for CSP

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Knowledge for Tomorrow

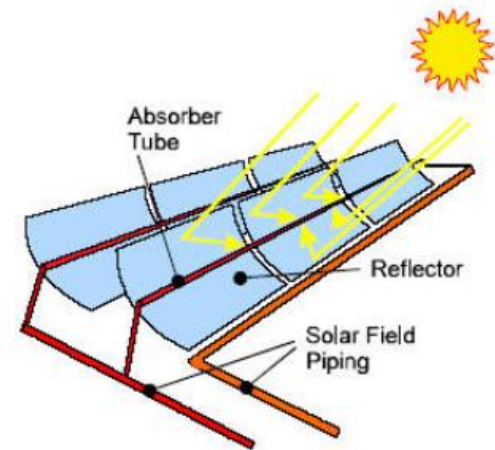
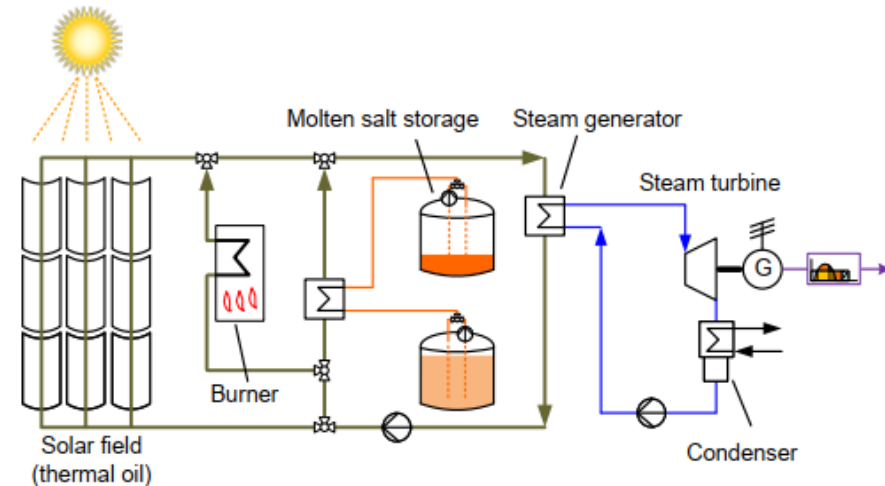


# Outline

- 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



# 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

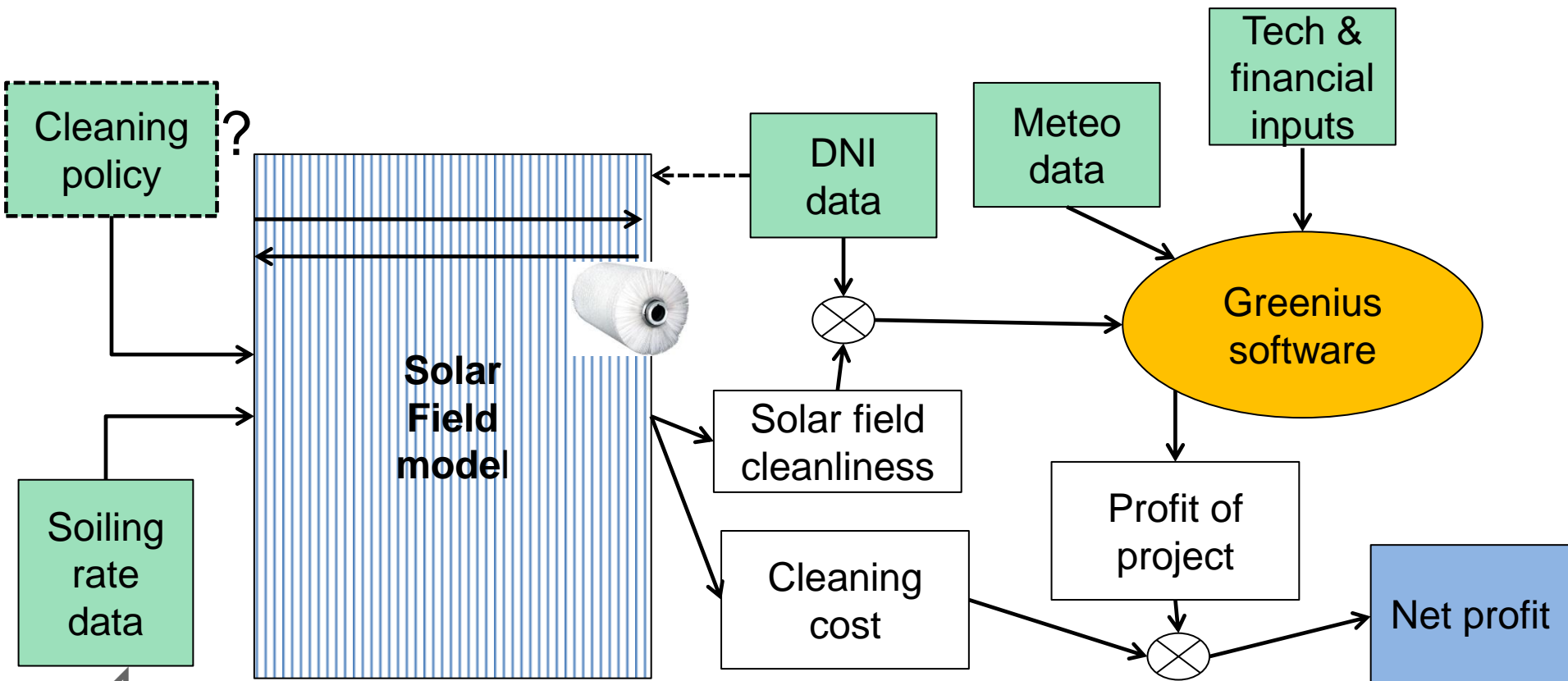


Soiled trough at PSA



# 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

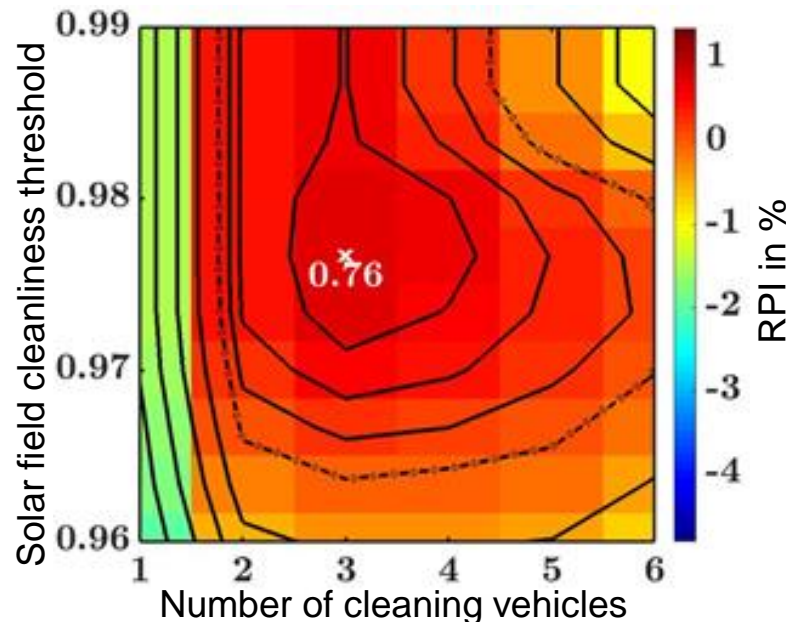
- 50 MW plant with 7.5 h storage
- Water and brush based cleaning vehicles
- Cleaning related technical and financial parameters (see table)
- Cleaning costs:
  - Labor, water, fuel, depreciation of cleaning vehicles
- **5 years** of soiling rate measurement data at PSA
- **>28 years** of irradiance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



Parameter	Value
Nominal turbine power	49,9 MW
Number of loops in Solar Field	156
Aperture area of solar field	510.000 m <sup>2</sup>
Thermal storage	7.5 h
Cooling	water
Planned lifetime	25 years
DNI-yearly sum at PSA	2388 kWh/m <sup>2</sup> /a
Equity ratio	30 %
Specific operating costs	1.8 EUR/m <sup>2</sup> /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 <sup>3</sup> /loop
Estimated lifetime of cleaning unit	15 years

# Cleaning optimization: policy comparison

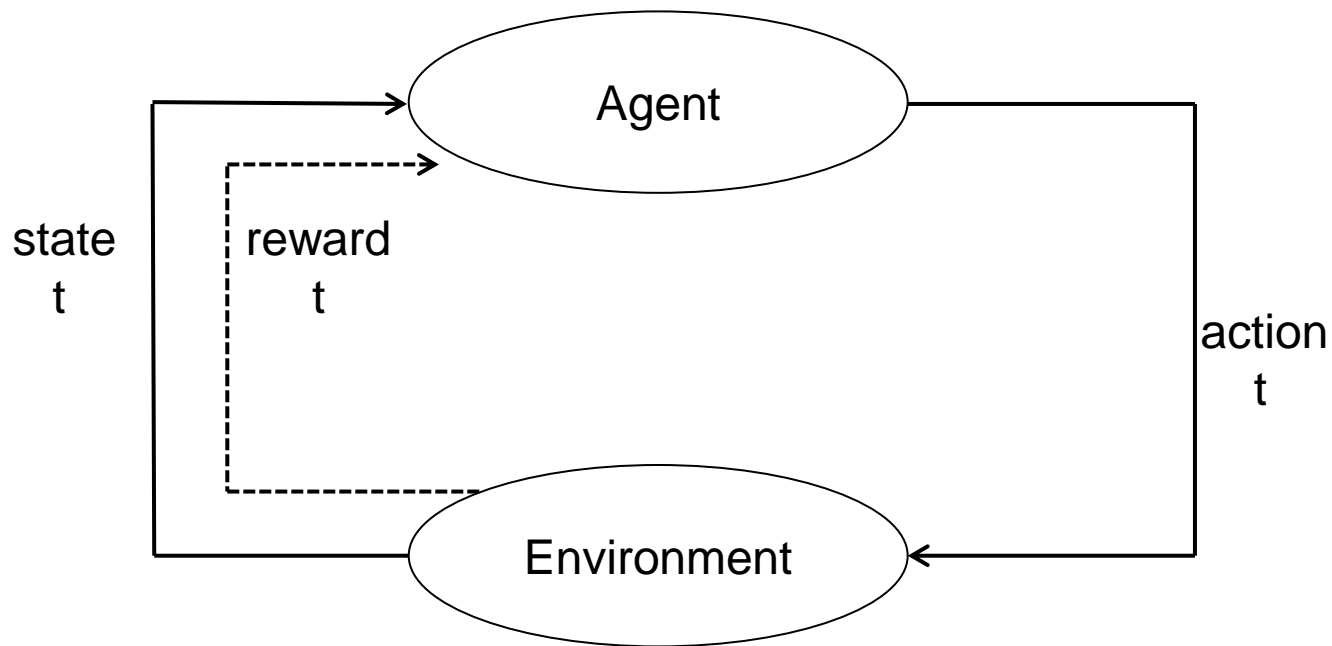
- A **reference cleaning strategy** is chosen as a reference point: constant, daily cleaning in one shift with 1 vehicle
- Cleaning policies are compared to reference by **relative profit increase (RPI)**
- **Previous study:** condition based cleaning policies:
  - Vary number of vehicles and cleanliness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



Can cleaning strategy be improved by reinforced Learning and forecast?

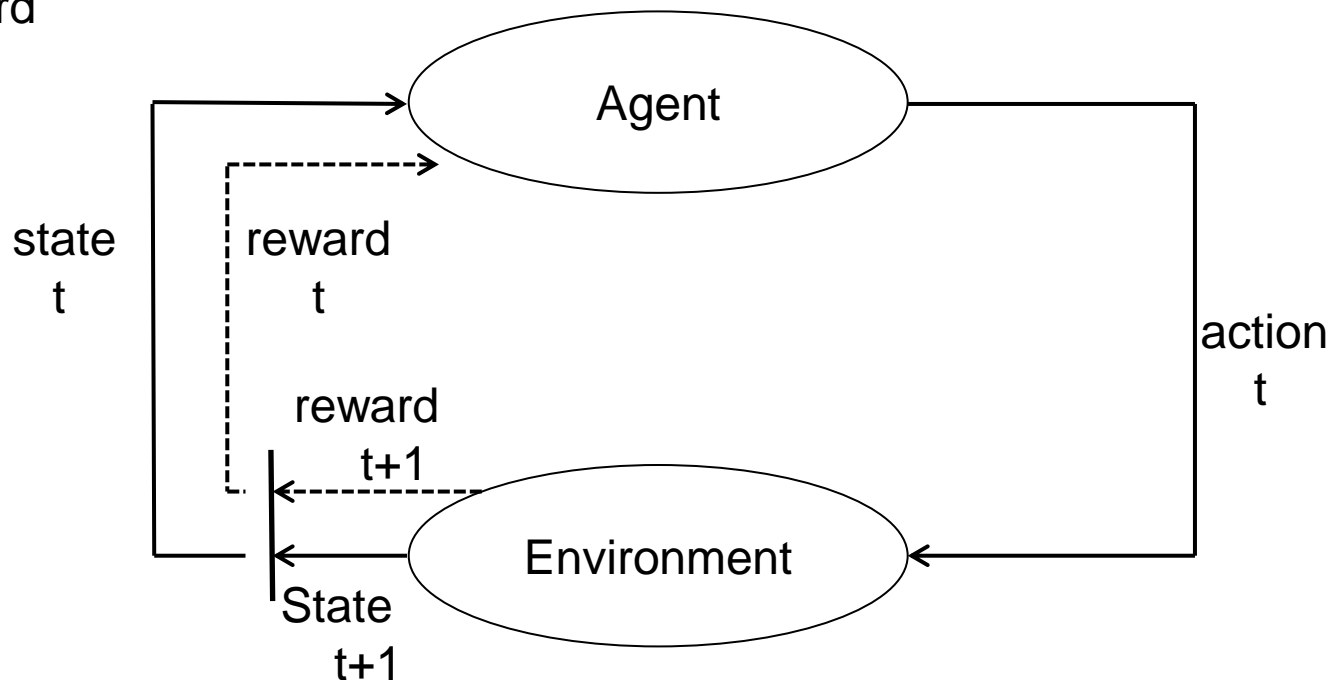
# Artificial Neural Networks: Reinforced learning

- Agent takes action depending on the environment



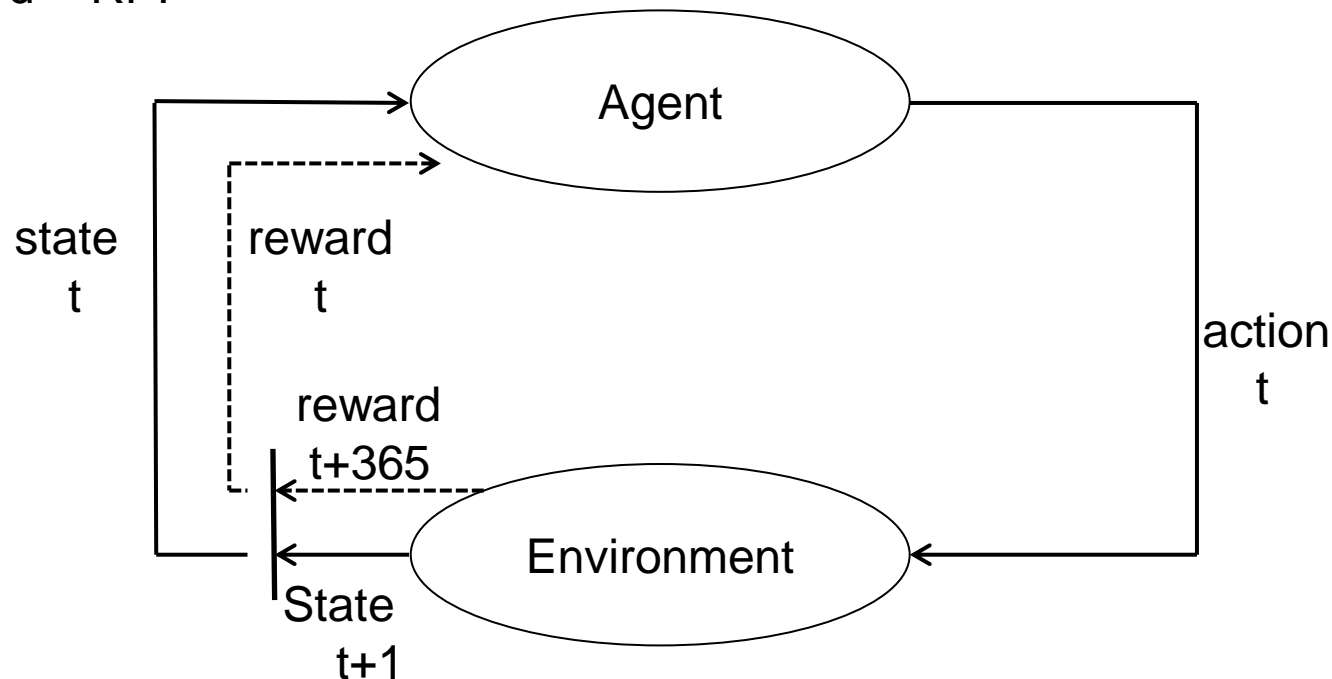
# Artificial Neural Networks: Reinforced learning

- 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

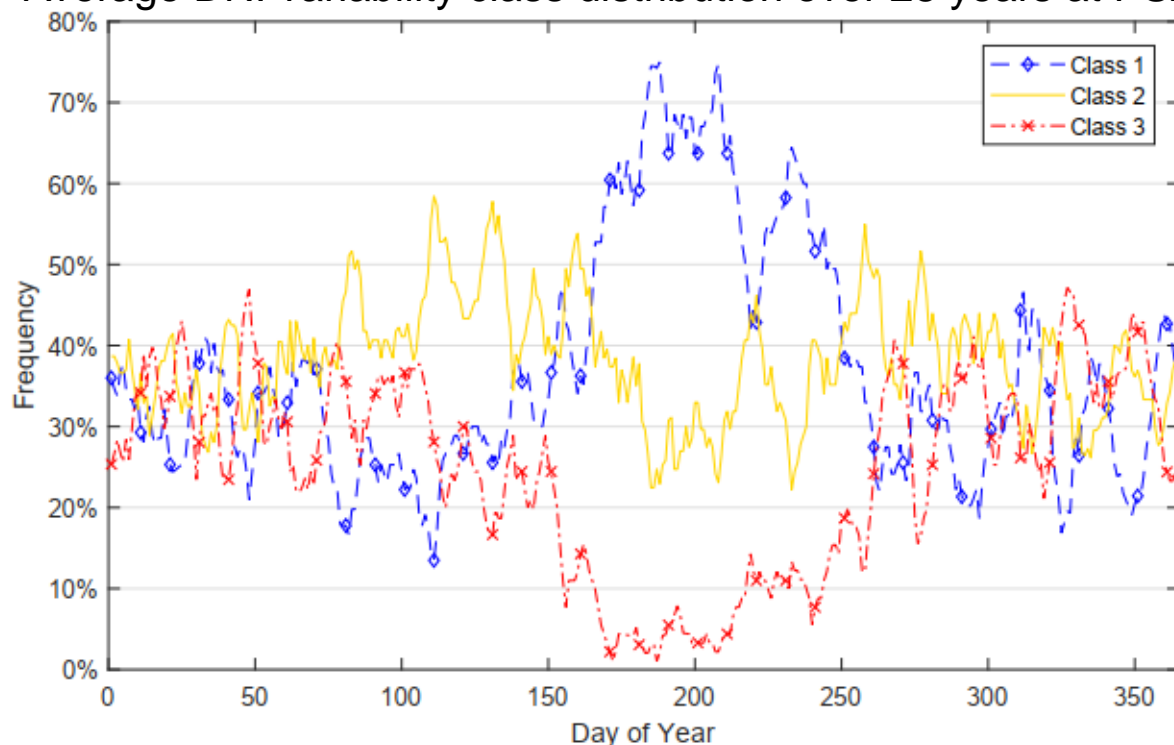
- Each training run involves full simulation year, i.e. 365 states and cleaning decisions
  - Option to provide agent with soiling rate and weather forecast information
  - Training of reinforced learning agent requires a **large amount of data**
  - 5 years of soiling data and 28 years of weather data 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) <sup>1</sup>
- **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

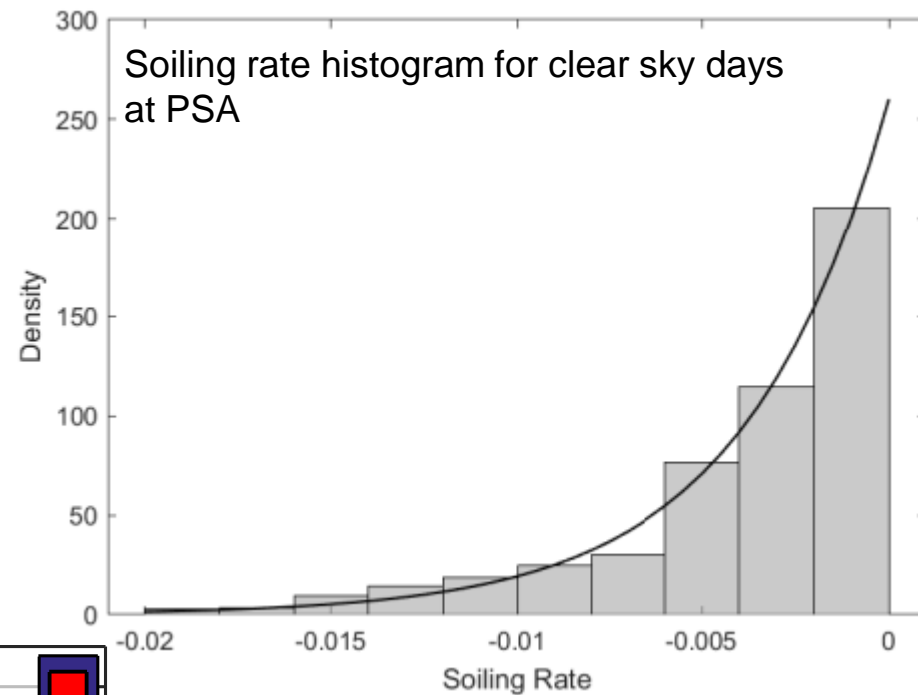
Average DNI variability class distribution over 28 years at PSA



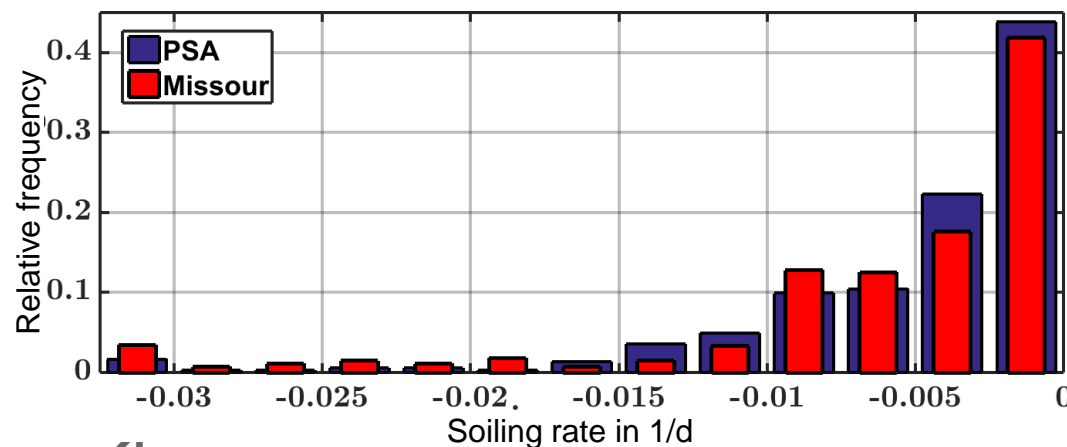
Current day \ Following day			
	Class 1	Class 2	Class 3
Class 1	58 %	32 %	10 %
Class 2	31 %	45 %	24 %
Class 3	17 %	38 %	45 %

# 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

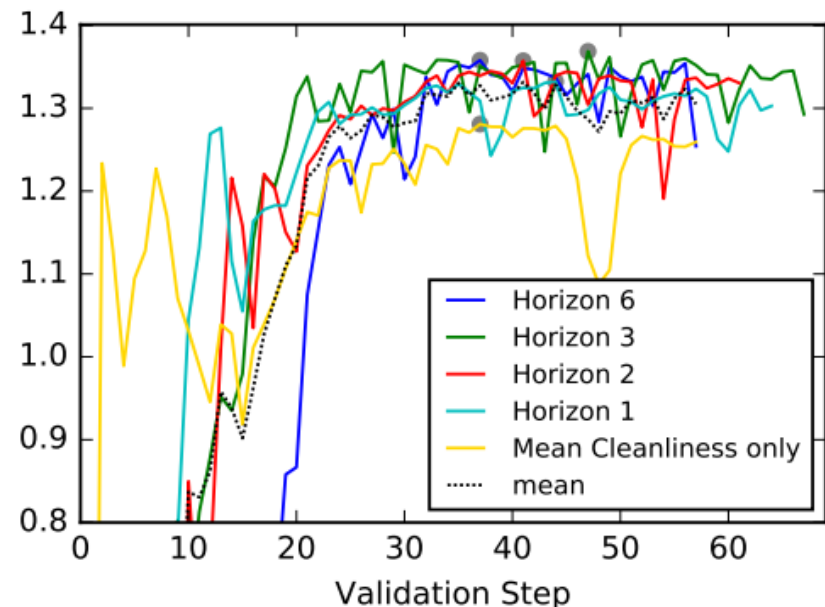
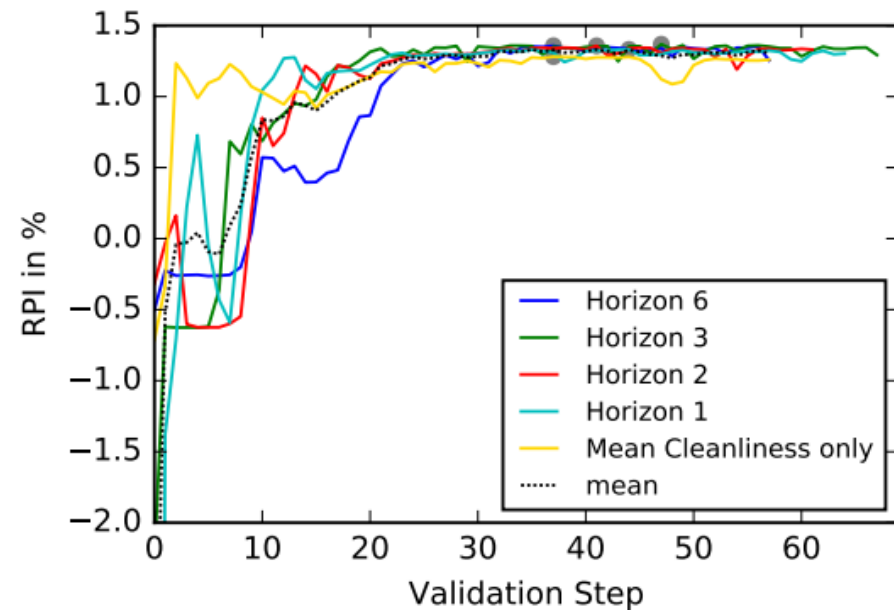


Soiling rate histograms for PSA and Missouri, Morocco and all classes



# 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



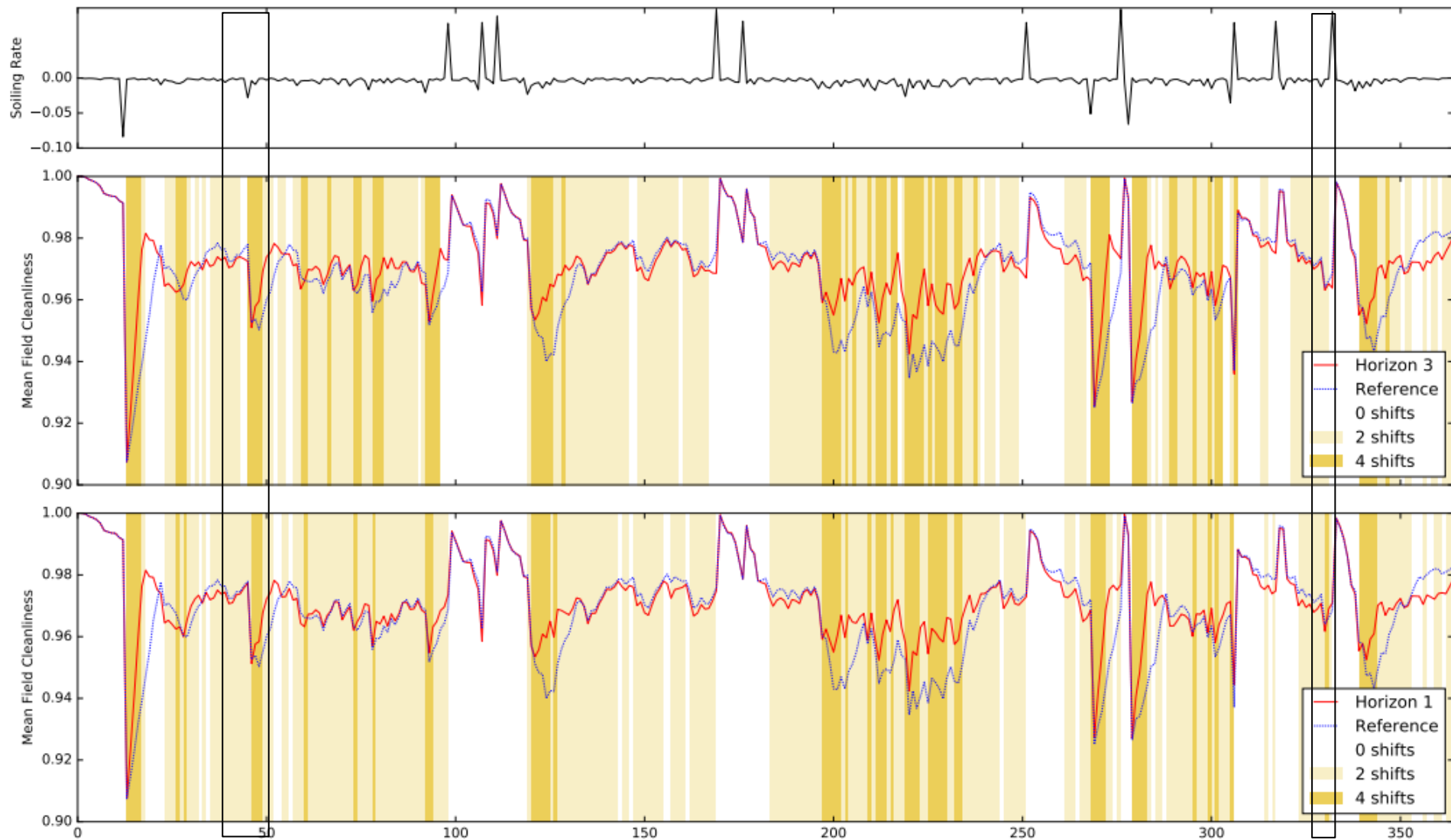
# Application of soiling forecast in cleaning policy: results

- 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



# 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](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

