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
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

Diagram:
- Cleaning policy
- Solar Field model
- Soiling rate data
- DNI data
- Meteo data
- Greenius software
- Tech & financial inputs
- Solar field cleanliness
- Cleaning cost
- Profit of project
- Net profit
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

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nominal turbine power</td>
<td>49.9 MW</td>
</tr>
<tr>
<td>Number of loops in Solar Field</td>
<td>156</td>
</tr>
<tr>
<td>Aperture area of solar field</td>
<td>510,000 m²</td>
</tr>
<tr>
<td>Thermal storage</td>
<td>7.5 h</td>
</tr>
<tr>
<td>Cooling</td>
<td>water</td>
</tr>
<tr>
<td>Planned lifetime</td>
<td>25 years</td>
</tr>
<tr>
<td>DNI-yearly sum at PSA</td>
<td>2388 kWh/m²/a</td>
</tr>
<tr>
<td>Equity ratio</td>
<td>30%</td>
</tr>
<tr>
<td>Specific operating costs</td>
<td>1.8 EUR/m²/a</td>
</tr>
<tr>
<td>Feed-in tariff</td>
<td>0.27 EUR/kWh</td>
</tr>
<tr>
<td>Cleaning velocity for one unit</td>
<td>9 loops / shift</td>
</tr>
<tr>
<td>Number of personnel per vehicle</td>
<td>1</td>
</tr>
<tr>
<td>Cleaning vehicle fuel consumption</td>
<td>6 – 8 l/loop</td>
</tr>
<tr>
<td>Cleanliness after cleaning</td>
<td>0.986</td>
</tr>
<tr>
<td>Demin. water consumption of cleaning unit</td>
<td>1 m³/loop</td>
</tr>
<tr>
<td>Estimated lifetime of cleaning unit</td>
<td>15 years</td>
</tr>
</tbody>
</table>

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) \(^1\)
- **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

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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
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.

<table>
<thead>
<tr>
<th>Forecast Horizon in days</th>
<th>RPI in [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ø</td>
<td>1.28</td>
</tr>
<tr>
<td>1</td>
<td>1.33</td>
</tr>
<tr>
<td>2</td>
<td>1.36</td>
</tr>
<tr>
<td>3</td>
<td>1.37</td>
</tr>
<tr>
<td>6</td>
<td>1.36</td>
</tr>
</tbody>
</table>
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:
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 soiling rate