# Data Analysis in Parabolic Trough Fields Determination of Mirror Cleanliness with Machine Learning

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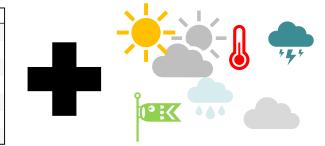
### **Motivation**

- Concentrated solar power (CSP) plants are located in arid regions with high dust loads
- Mirrors need to be cleaned frequently to maintain high reflectivity
- Knowledge about cleanliness of mirrors is crucial for cleaning decision
- Cleanliness usually measured with hand-held devices
  - Accurate but costly

# **Objectives**

- Development of an alternative method to estimate the cleanliness of individual collectors
- Optimization of the cleaning schedule towards a demand oriented schedule based on model predictions
- Only operational data from the power plant and meteorological data available at the site are used
  - Easy and cheap implementation without additional hardware requirements
- Which model inputs have the biggest influence on the model prediction?

|         | Loc  | TimeStamp           | LocMode | SCAAngle | Temperature1 |
|---------|------|---------------------|---------|----------|--------------|
| 0       | LB05 | 2015-05-14 08:00:00 | 8       | 10.27    | 200.22       |
| 1       | LG03 | 2015-05-14 08:00:00 | 8       | 10.08    | 202.49       |
| 2       | LC05 | 2015-05-14 08:00:00 | 8       | 10.16    | 199.55       |
| 3       | LF05 | 2015-05-14 08:00:00 | 8       | 10.41    | 200.61       |
| 4       | LB07 | 2015-05-14 08:00:00 | 8       | 9.21     | 199.30       |
|         |      |                     |         |          |              |
| 2430067 | LA30 | 2015-05-14 19:59:59 | 8       | 166.43   | 315.31       |

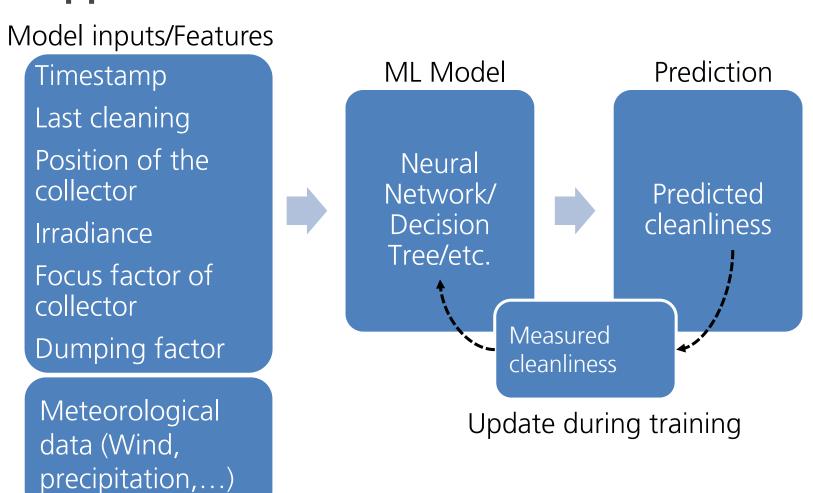








# Approach & Methods



### **Models**

- Machine Learning models: Neural Network (NN), Decision Tree (DT), Gaussian Processes (GP), Support Vector Regression (SVR), Linear Regression (LR)
- Models are trained with datasets of different sizes
  - Models should be adaptable to different CSP plants with changing data availability

#### **Metrics for model evaluation**

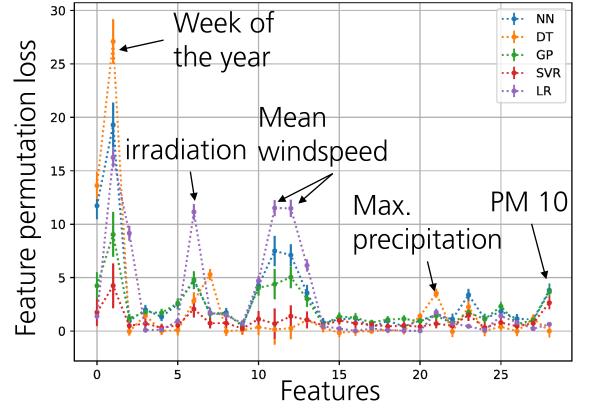
- Comparison with reference cleanliness measurements (optimal outcome is a perfect fit of the reference measurements)
- Comparison with cleaning schedule (only a classification of mirror cleanliness between clean/soiled required)
- Feature Permutation Loss used as method to estimate the influence of different model inputs
- Uncertainties of model predictions are taken into account via multiple model runs (systematic uncertainty) and confidence intervals (statistic uncertainty)

### Results

#### **Optimizing cleaning schedule** 0.79 0.80 Cleaning schedule 8.0 0.6 0.2 0.03 0.04 0.01 ΤN Τ̈́P ĖΝ 0.79 0.8 0.6 0.4 0.18 0.2 0.07 0.04 F1-score Precision Recall Accuracy

- Too early cleanings can be reduced by 14.3 %
- Necessary cleanings are detected in 12.2 %

more cases



High influence of temporal feature in accordance with high seasonality of soiling

# **Comparison with reference measurements** predicted $R^2 = 0.77$ $R^2 = 0.74$ predicted $R^2 = 0.52$ 75 actual predicted ® 6 $R^2 = 0.34$ actual

- Best results are achieved with Decision Tree model using the biggest dataset (operational and meteorological data)
  - 77 % of the data can be explained by the model
- Neural Network and Decision Tree both show good results with different dataset sizes
  - Beneficial for model integration in other power plants with different measurement setup

# **Summary & Outlook**

# **Key results**

- Operational data and meteorological data can be used to build a model for cleanliness determination
- Optimizing the cleaning schedule is easier task
- Best results for Decision Trees, followed by Neural Networks

### **Related work**

- Similar approaches for photovoltaic are available, but they are not directly applicable (2)
- Physical models for CSP Systems are available, but they require meteorological data and they do not use operational data from solar field (3)

### **Ongoing and future work**

Cleanliness determination:

• Predicting average values for entire subfield with Convolutional Neural Networks

### Flow determination:

- Using "time-of-flight" measurements from temperature deviation in solar field to calculate flow Anomaly detection:
- Using Autoencoders to detect and locate anomalies in parabolic trough fields

### References

- (1) Parabolic trough at Plataforma Solar de Almería (Owned by the Spanish research center CIEMAT), Source DLR
- (2) W. Javed et al., Modeling of photovoltaic soiling loss as a function of environmental variables, Solar Energy 157 (2017) 397–407
- (3) G. Picotti et al., Development and experimental validation of a physical model for the soiling of mirrors for csp industry applications, Solar Energy 173 (2018) 1287-1305



