Soiling Losses for Concentrating Solar Power – Prediction, Assessment, and Mitigation

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Outline

• Introduction
• Soiling modelling & prediction
• Experimental activities & model prediction assessment
• Model enhancement & characterizing prediction uncertainty
• Cleaning optimization: balancing cleaning costs & reflectance losses
• HelioCon soiling subtask
• Conclusions
Who are we? ASTRI Node 5 (QUT/Flinders)

P5.4 Operation & Maintenance

- Reliability Engineering
- Dynamic systems & control
- Maintenance optimisation

- Soiling modelling & analysis
- Heliostat cleaning optimisation
- Receiver thermal modelling

- Condition-based Maintenance
- Heliostat cleaning optimization

- Condition-based Maintenance
- Heliostat cleaning optimization

- Materials Engineering
- Corrosion characterization

- Materials Engineering
- Corrosion characterization

- Materials characterisation
- Corrosion analysis
- Solid Mechanics

P5.3 Advanced Materials

- Nanoscience
- Coatings

- Soiling modelling & analysis
- Heliostat cleaning optimisation
- Anti-soiling coatings & dust analysis

- Soiling & experimental dust analysis
- Anti-soiling coatings & dust analysis

- Materials characterisation
- Corrosion analysis
- Solid Mechanics
Soiling losses for CSP plants

- Loss of reflectance can be an important detrimental factor in solar tower plant productivity
- Losses between 0.3%-3% per day reported*,**,  
- Cleaning costs and productivity losses due to soiling have both a significant and comparable costs in some locations  
- TEA shows significant effect of field reflectance on LCOH

* A. Alami Merrouni, et al. (2020) CSP performance and yield analysis including soiling measurements for Morocco and Portugal, Renewable Energy 

Preliminary results from Chad Augustine’s Technoeconomic Analysis Seminar

https://helioscsp.com/tag/cleaning-systems-for-heliostats/
Soiling & cleaning work at QUT

1. Goal: develop and understanding of how/why soiling rates vary, predict them, and plan mitigation at site selection

2. Developing a **physical model** for soiling that enables prediction of soiling rates for potential and current sites.

3. Undertaking **experimental activities** to 1) characterize soiling processes at different sites; 2) compare and characterize measurement techniques; 3) estimate parameters and validate soiling model predictions.

4. Developing **cleaning strategies** that optimally balance the cost of cleaning with production. Two main approaches:

   - a **time-based** approach, which identifies an optimal cleaning schedule based on reflectance losses predictions
   - a **reflectance-based** approach, where reflectance threshold(s) trigger cleaning.
Soiling modelling & prediction
Soiling losses for CSP plants

• Purely physical models too detailed, slow, and challenging to parameterize

• Many existing models based on regression or AI (e.g. ANN)*,**

• Nice part of this: reasonable predictions for a site without too much effort!

• Challenges with this approach:
  • Physical meaning lost
  • Little hope of extrapolation to other sites
  • Bad predictions hard to diagnose — only remedy is “more data”

• Our ongoing developments are moving toward a compromise — a “semi-physical” approach

* Bonanos, et al. (2019), Characterization of Mirror Soiling in CSP Applications, SolarPACES 2019
** Conceição, and Collares-Pereira (2018), CSP Mirror Soiling Characterization and Modeling, Solar Energy Materials and Solar Cells
Key processes

Generation

Lifting, saltation, & transport

- Challenging to have predictive models at local levels
- Large number of parameters and global scale of the processes
- Measuring dust can “short-circuit” need for detailed generation model

Soiling model overview*

**

- Deposition
  - Gravity
  - Turbulence and inertia

- Adhesion
  - van der Waals

- Removal
  - Gravity

- Reflectance Loss


Deposition

The resistance model

Deposition Velocity

\[ v_d = f(d, v_g, r_a, r_b) = v_g + \frac{1}{r_a + r_b} \]

Dust Flux

\[ F_t(d) = C_d \cdot v_d \quad \text{[kg m}^2\text{s}] \]

<table>
<thead>
<tr>
<th>Units</th>
<th>Description</th>
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<tbody>
<tr>
<td>(d)</td>
<td>(\mu\text{m})</td>
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<tr>
<td>(C_d)</td>
<td>(\text{number m}^3)</td>
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<tr>
<td>(v_g)</td>
<td>(\text{m s}^{-1})</td>
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<tr>
<td>(r_a)</td>
<td>(\text{s m}^{-1})</td>
</tr>
<tr>
<td>(r_b)</td>
<td>(\text{s m}^{-1})</td>
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*Seinfeld and Pandis (2016), Atmospheric Chemistry and Physics: From Air Pollution to Climate Change.
Deposition

Terminal velocity (from force balance)

\[ v_g = \begin{cases} \frac{d^2 \rho g C_c}{18 \mu_a} & \text{Re} < 0.1 \\ \left( \frac{4d \rho g C_c}{3C_D \rho a} \right)^{0.5} & \text{Re} \geq 0.1 \end{cases} \]

<table>
<thead>
<tr>
<th>Units</th>
<th>Description</th>
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<tbody>
<tr>
<td>( \rho )</td>
<td>( \frac{\text{kg}}{\text{m}^3} )</td>
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<tr>
<td>( C_c )</td>
<td>–</td>
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<tr>
<td>( C_D )</td>
<td>–</td>
</tr>
<tr>
<td>( \mu_a )</td>
<td>( \frac{\text{N} \cdot \text{s}}{\text{m}^2} )</td>
</tr>
</tbody>
</table>
\[
E_b = Sc^{-1/2} \quad E_{im} = \frac{St^2}{400 + St^2} \quad R_1 = \exp(-St^{1/2})
\]

Expressions for \( r_a \) and \( r_b \) depend on land use / atmospheric conditions.

<table>
<thead>
<tr>
<th>Units</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( U )</td>
<td>Wind speed</td>
</tr>
<tr>
<td>( D )</td>
<td>( \frac{k_b T_c C_c}{3 \pi \mu_a d} ) Brownian diffusivity of particles</td>
</tr>
<tr>
<td>( u_* )</td>
<td>Friction velocity = ( \frac{kU}{\ln \left( \frac{z}{z_0} \right)} )</td>
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<tr>
<td>( \nu_a )</td>
<td>Kinematic viscosity of air</td>
</tr>
<tr>
<td>( Sc )</td>
<td>Schmidt number = ( \frac{\nu_a}{D} )</td>
</tr>
<tr>
<td>( St )</td>
<td>Stokes number = ( \frac{\nu_a u_*^2}{\nu_a g} )</td>
</tr>
<tr>
<td>( \kappa, k_b )</td>
<td>(-\frac{1}{K}) von Karman and Boltzman constants</td>
</tr>
</tbody>
</table>
Soiling Model

Adhesion vs gravity moments

Force of Adhesion (van der Waals)

Dust particles are assumed to be rigid spheres made of Silica

Removal is assumed to be due to gravity-induced rolling

Condition for removal for particle of diameter $d$:

$$M_{\text{removal}}(\alpha_t, d) > M_{\text{adhesion}}(\alpha_t, d)$$
Reflectance Loss

Reflectance is a function of the incidence angle \( \theta \)

- First surface vs. second surface\(^*,\)**
- Second surface is more likely for solar mirrors
- Assuming: 1) the reflectance loss is not too high; 2) that \( \theta \) is “far enough” from zero or 90°
- The soiled reflectance is approximately

\[
\rho_t = \rho_0 \left(1 - \frac{2A_{soil,t}}{\cos(\theta)A_{mirror}}\right)
\]

Where \( A_{soil,t} \) is the particle area at \( \theta = 0 \)

Soiling Model

Putting it all together

\[ v_d(d, U_t, T_t) = v_g + \frac{1}{r_a + r_b} \]

\[ F_t(d, U_t, T_t) = C_t(d) \cdot v_d \cdot \cos(\alpha_t) \]

\[ n_t(d) = \int_{t_0}^{t} F_t(d, U_t, T_t) \, d\tau \quad \text{(number dist. on mirror)} \]

**Deposition**

\[ d_c = \min d \]

s.t. \( M_{\text{adhesion}}(\alpha_t, d) < M_{\text{removal}}(\alpha_t, d) \)

\[ m_t(d \geq d_c) = 0 \]

**Adhesion/Removal**

\[ A_{\text{soil},t} = \frac{\pi}{4} \int_0^{d_c} \delta^2 \cdot n_t(\delta) \, d\delta \]

\[ A_{\text{soil},t} \approx \frac{2A_{\text{soil},t}}{\cos(\theta_t)} \]

\[ \rho_t = \rho_0 \left( 1 - \frac{A_{\text{soil},t}(\theta_t)}{A_{\text{mirror}}} \right) \]

**Reflectance Loss**

Assumed dust distribution to convert from single measurement \( \rightarrow C_t(d) \)
Predicting reflectance using the model

Inputs:

- Discretize into intervals $t = t_0 + k\Delta t$, assume deposition velocity is constant in this time
- Sample weather variables at beginning of each interval: $(U_k, T_k, PM_{x,k})$ $k = 1, 2, \ldots, K$
- Measure dust concentration $PM_{x,k}$ (This is TSP if $x \rightarrow \infty$)
- Average tilts over each interval, $\alpha_k$
- Prototype dust distribution $\hat{n}(D)$ (and a corresponding $\overline{PM}_x$)
- Known roughness height parameter $hrz0 = \frac{z}{z_0}$ (property of site and measurement setup)

\[
\mu(U_k, T_k; hrz0) = \frac{\pi}{4} \int_0^{d_c} D^2 \cdot v_d(D, U_k, T_k) \cdot \hat{n}(D) dD \quad \text{Area loss of a flat mirror when } PM_{x,k} = \overline{PM}_x
\]
Predicting reflectance using the model

Inputs:
- Discretize into intervals \( t = t_0 + k \Delta t \), assume deposition velocity is constant in this time
- Sample weather variables at beginning of each interval: \((U_k, T_k, c_k)\) \( k = 1,2, ..., K \)
- Measure dust concentration \( PM_{x,k} \) (This is TSP if \( x \to \infty \))
- Average tilts over each interval, \( \alpha_i \)
- Prototype dust distribution \( \hat{n}(D) \) (and a corresponding \( PM_x \))
- Known roughness height parameter \( h_{rz0} = \frac{z}{z_0} \) (property of site and measurement setup)

\[
\hat{A}_{\text{soil},k} \approx \sum_{i=0}^{k-1} \frac{PM_{x,i}}{PM_x} \cdot \cos(\alpha_i) \cdot \mu(U_i, T_i; h_{rz0}) \quad \text{Cumulative area loss since } t_0
\]

\[
\hat{\rho}_k = \rho_0 \left( 1 - \frac{2\hat{A}_{\text{soil},k}}{\cos(\theta_k) A_{\text{mirror}}} \right) \quad \text{Reflectance at incidence angle } \theta_k
\]
Recent developments: a stochastic loss model

Recently, we’ve been exploring the use of a stochastic model to try to assess prediction uncertainty

$$\hat{A}_{soil,k} \approx \sum_{i=0}^{k-1} \frac{PM_{x,i}}{PM_x} \cdot \cos(\alpha_i) \cdot [\mu(U_i, T_i; hrz0) + \epsilon_i]$$

where $\epsilon_i \sim \mathcal{N}(0, \sigma_{dep}^2)$ are independent noise terms. This model has two parameters: $hrz0$ and $\sigma_{dep}^2$. We also assume that the reflectance measurement at time index $k_i$ is uncertain:

$$r_{k_i} = \hat{\rho}_{k_i} + \epsilon_{k_i}$$

with $\epsilon_{k_i} \sim \mathcal{N}(0, \sigma_{m,k_i}^2)$ is the uncertainty for the reflectance measurement...
Fitting the free parameter $hrz0$

- $hrz0$ is a function of the site under our previous assumptions
- Reflectance measurements $r_{ki}$ $i = 1, 2, \ldots, N$ available

$$
\hat{hrz0} = \arg\min_{h>1} [r_{ki} - \hat{\rho}_k(h)]^2
$$

$\hat{hrz0}, \hat{\sigma}_{dep} = \arg\max_{h>1} \sum_{i=1}^{N} \log p(r_{ki} - r_{ki-1} | h, \sigma_{dep}^2)$

where $p(r_{ki} - r_{ki-1} | h, \sigma_{dep}^2)$ is the probability density function of the changes (it can be shown that this is Gaussian)
Soiling model available on GitHub

- https://github.com/cholette/HelioSoil
- Tutorial paper forthcoming in SolarPACES (hopefully!)
- Stochastic model not yet in there, but it will be soon
- Data from QUT experiments is also up there
- Development is active and will continue for some time
Experimental activity & model prediction assessment
Soiling Rig #1 — QUT

Acceptance Angle: 4.6-46 mrad
Wavelength: 0.4-0.8 µm
Incidence Angle: 15°
Repeatability: ± 0.2%
Performance of the model on QUT data

Used for fitting

Different degradation rates due to different wind/airborne dust
Prediction of tilt effects is quite good.
Early results from stochastic model are promising.
Soiling Rig #2 — Mount Isa, Queensland

- Installation of dust and weather monitoring station
- Deployment of mirror test rig with 18 differently tilted and oriented samples
- Measurements taken with a D&S reflectometer twice a day for one week

Acceptance Angle: 4.6-46 mrad
Wavelength: 0.4-0.8 µm
Repeatability: ± 0.2%
**Example Data**

*Mount Isa*

- Sample data on the right
- TSP and wind speed available
- No rain
- No relative humidity sensor
- Losses are between 0 (vertical) and 0.02 during the experiment for the six mirrors that we’ll look at
Performance of model in Mount Isa

3/18 mirrors used for fitting on first 5 days

Only 7/18 mirrors shown here for brevity!
Testing on a subsequent experiment (Mount Isa)
Soiling Rig #3 — Wodonga, Victoria

- 5 mirrors facing East and West
- Tilted at 0°, 5°, 30°, 30°, 60°

Dust sampler measures five different PMx fractions
Soiling Summary

• Models developed have reasonable agreement with experiments

• Ongoing data collection will help assess impact of different assumptions (e.g. size distributions)

• Other experimental activities:
  • Comparison of measurement techniques for (artificially) soiled mirrors (right)*
  • Moisture effects on deposition (this July 2022 at Fraunhofer ISE)

Cleaning optimization
Cleaning optimization

Total cleaning costs

- Early work in fixed-frequency cleaning of entire field assumes deterministic (average) losses
- But, soiling is uneven across field, can be highly stochastic, and have seasonal statistical properties
- Given the dust-in-air of a site, need to decide on cleaning resources (trucks, people, etc.) and timing of cleanings of different sectors
- Some approaches:
  - a time-based approach, which identifies an optimal cleaning schedule based on reflectance losses predictions
  - a reflectance-based approach, where reflectance threshold(s) trigger cleaning
Cleaning optimization

Total cleaning costs

Optimal cleaning minimized the total cleaning cost:

\[ TCC = C_{\text{variable}} \cdot n_{\text{cl}} + C_{\text{fixed}} \cdot n_{\text{trucks}} + C_{\text{deg}} \]

where \( C_{\text{variable}} \) includes water, fuel, etc., and \( C_{\text{fixed}} \) is mostly depreciation of the trucks and operator salaries.

\[ C_{\text{deg}} = \sum_{i=1}^{T} \sum_{j=1}^{N_s} \eta_{\text{opt},ij} \cdot (1 - f_{\text{soil},ij}) \cdot A_j \cdot DNI_i \cdot \eta_{\text{th},i} \cdot \eta_{\text{pb}} \cdot \rho_i \]

(clean) optical efficiency at time interval \( i \) for sector \( j \)
Cleaning optimization

Total cleaning costs

Optimal cleaning minimized the *total cleaning cost*:

\[
TCC = C_{\text{variable}} \cdot n_{cl} + C_{\text{fixed}} \cdot n_{\text{trucks}} + C_{\text{deg}}
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\]

Soiling factor (from the + perfect cleans) for each sector/time
## Cleaning optimization

### Total cleaning costs

Optimal cleaning minimized the total cleaning cost:

\[ TCC = C_{\text{variable}} \cdot n_{\text{cl}} + C_{\text{fixed}} \cdot n_{\text{trucks}} + C_{\text{deg}} \]

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Area of sector \( j \) and DNI at time interval \( i \)
Cleaning optimization

Total cleaning costs

Optimal cleaning minimized the total cleaning cost:

$$TCC = C_{variable} \cdot n_{cl} + C_{fixed} \cdot n_{trucks} + C_{deg}$$

where $C_{variable}$ includes water, fuel, etc., and $C_{fixed}$ is mostly depreciation of the trucks and operator salaries.

$$C_{deg} = \sum_{i=1}^{T} \sum_{j=1}^{N_s} \eta_{opt,ij} \cdot (1 - f_{soil,ij}) \cdot A_j \cdot DNI_i \cdot \eta_{th,i} \cdot \eta_{pb} \cdot p_i$$

Thermal efficiencies of receive and power block
Cleaning optimization

Total cleaning costs

Optimal cleaning minimized the total cleaning cost:

\[ TCC = C_{variable} \cdot n_{cl} + C_{fixed} \cdot n_{trucks} + C_{deg} \]

where \( C_{variable} \) includes water, fuel, etc., and \( C_{fixed} \) is mostly depreciation of the trucks and operator salaries.

\[ C_{deg} = \sum_{i=1}^{T} \sum_{j=1}^{N_s} \eta_{opt,ij} \cdot (1 - f_{soil,ij}) \cdot A_j \cdot DNI_i \cdot \eta_{th,i} \cdot \eta_{pb} \cdot p_i \]
Cleaning Optimization – Time Based*

MILP Optimization
699 cleanings – 2 trucks – TCC = 1.60M$

Heuristic Optimization (sweep trucks & annual cleans and take minimum)
672 cleanings – 2 trucks – TCC = 1.66M$

MILP provides “perfect knowledge” solution as a benchmark (not implementable)
Heuristic is close and is implementable without knowledge of future soiling.

Cleaning Optimization

Reflectance Based*,**

- Reflectance measurements can be used to trigger cleaning
- Cleaning policy maps sectorial reflectances to a cleaning decision at each time
- Policy parameters optimized via (approximate) dynamic programming (ADP)
- ADP exploits stochastic simulation enabled by physical model and historical weather data.

Cleaning Optimization

Reflectance Based*,**

Picking the right cleaning resources is key decision if resources are “owned”


Soiling Losses for Concentrating Solar Power | Michael E. Cholette
HelioCon Soiling Subtask
Soiling subtask

Scope

• Concerned with the development of soiling measurement, modelling, and mitigation techniques to characterize soiling losses and plan mitigation measures for existing and planned CSP plants

• Key areas:
  • Soiling measurements
  • Modelling and characterizing soiling processes
  • Mitigation (including cleaning and coatings)
State of the art

Measurements

- Portable reflectometers and sampling are a common approach
- A few automated (AVUS, TraCS, drones), few utilized commercially
State of the art

Modelling and characterizing soiling processes

• Soiling losses during site selection are highly uncertain
• Mostly regression analysis, but a few physical models have been developed (mostly resistance-like models)
• Many unvalidated simplifying assumptions (moisture ignored, spherical particles)

State of the art

Mitigation

• Studies on cleaning systems typically limited to small studies on prototype systems

• Anti-soiling coatings seem effective in some cases, but durability remains a question

• Economics of cleaning solar fields have been addressed quite thoroughly, but interaction with plant design is still not well explored

From: Wales et al., Optimizing vehicle fleet and assignment for concentrating solar power plant heliostat washing, IISE Transactions
### Soiling subtask

#### Top gaps

Develop methods to quickly assess if soiling may be a problem at a site

<table>
<thead>
<tr>
<th>Conceptual Design</th>
<th>Components</th>
<th>Integrated Heliostat</th>
<th>Mass Production</th>
<th>Deployed Field</th>
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</thead>
<tbody>
<tr>
<td><strong>So5</strong>: Soiling evaluation at site selection</td>
<td>So14: No standard or data to assess anti-soiling coating durability/performance</td>
<td></td>
<td></td>
<td>So13: Design and automation of new cleaning systems is underexplored</td>
</tr>
</tbody>
</table>

So15: Trade-offs between soiling losses, cleaning regime, design choices (e.g., site selection, solar multiple), and heliostat reliability are poorly understood
Conclusions
Conclusions

• Reported soiling losses for CSP vary widely — both in literature and in practice
• Models have been developed with some reasonable accuracy after the have been “tuned” to site
• Mitigation measures have mostly explored the balance between cleaning costs and lost production under exiting technologies
• Mitigation outcomes are clear: get the right cleaning resources if you own them.
• Caveat: If you are “contracting out” cleaning, you might need to be a bit more careful about timing
Conclusions

What’s next?

• Soiling modelling & assessment:
  • Model improvements and getting rough parameters without experiments
  • Development of a standard site characterization methodology
  • Update, maintain, and refine use cases for Python soiling library

• Soiling subtask
  • Release roadmap report
  • Develop recommended pathways for addressing key gaps
Questions?

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More From HelioCon

- Past seminar presentations now available on the NREL YouTube learning channel: https://www.youtube.com/playlist?list=PLmIn8Hncs7bGAK-hlf4qxyAbHUHK-xgZK
- Slides available here: https://drive.google.com/drive/folders/1162LN82ImgurpC0DnJDLKsERCWo-698R?usp=sharing
- Subscribe to the seminar series or get in touch: heliostat.consortium@nrel.gov

Next Seminar July 13th!

HelioCon Seminar Series: Heliostat Aerodynamics and Wind Load: Measurements, Characterization, and Prediction in Atmospheric Boundary Layer
Speaker: Dr. Matthew Emes, AU
When: 4-5pm MDT Wednesday July 13th
Zoom: https://nrel.zoomgov.com/j/1600359585?pwd=VENUTG9BK0J1T2xhazh0Y1JDRXl6QT09