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

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ASTRI

Australian Solar Thermal Research Institute

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

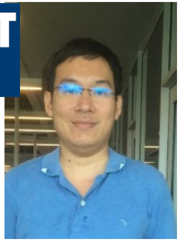
A/Prof. Michael Cholette

- Reliability Engineering
- Dynamic systems & control
- Maintenance optimisation

Dr Giovanni Picotti

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

Dr Huy Truong-Ba



- Condition-based Maintenance
- Heliostat cleaning optimization

P5.3 Advanced Materials

Prof. Ted Steinberg

- Materials Engineering

A/Prof. Geoff Will

- Corrosion characterization

Navid Mohammadzadeh

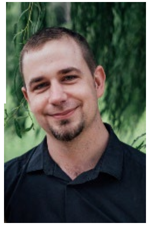
- CSP Dispatching

Cody Anderson

- Soiling & experimental dust analysis

Schannon Hamence

Flinders UNIVERSITY



- Anti-soiling coatings & dust analysis

Prof. David Lewis

Flinders UNIVERSITY

- Nanoscience
- Coatings

Dr Madjid Moghaddam

- Materials characterisation
- Corrosion analysis

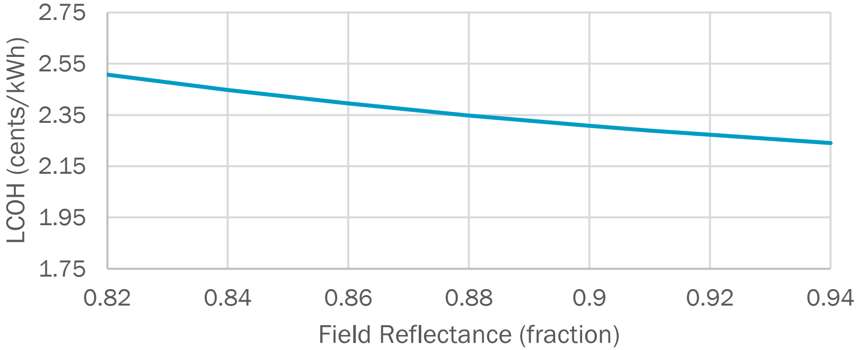
Dr Stuart Bell

- 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

https://helioscsp.com/tag/cleaning-systems-for-heliostats/



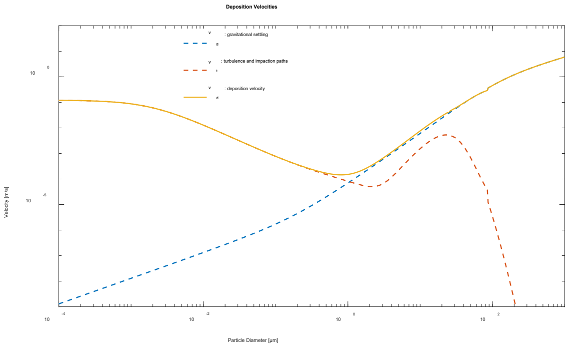
Preliminary results from Chad Augustine's Technoeconomic Analysis Seminar

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

** Klemens Ilse, et al. (2019) Techno-Economic Assessment of Soiling Losses and Mitigation Strategies for Solar Power Generation, Joule

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

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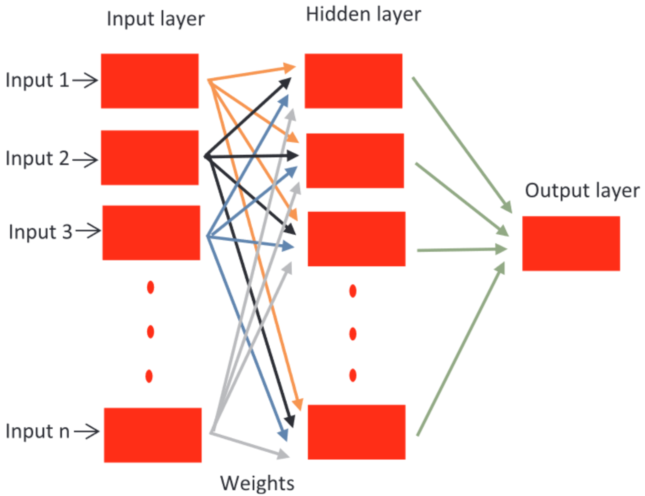
Soiling losses for CSP plants

- 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



From **

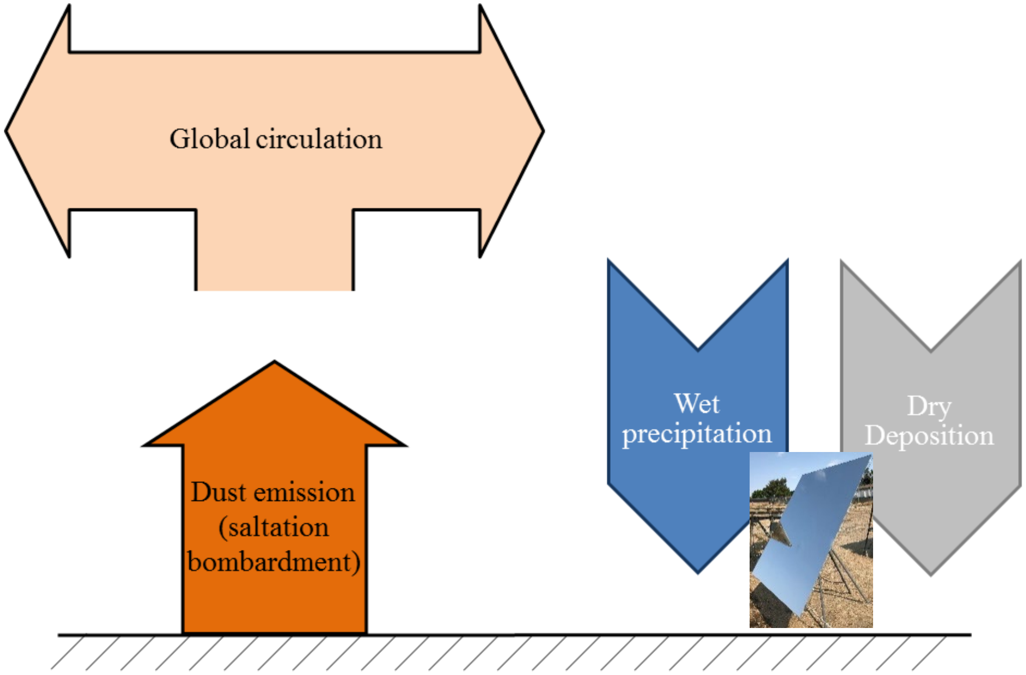
$$\Delta R_3 = 28.735 - 24.98\,x_1 - 0.031692\,x_2 - 0.23935\,x_3 - 4.4108\,x_4 - 0.1476\,x_5 - 0.0041501\,x_6 + 0.26417x_7 - 0.5433\,x_8 - 0.60992\,x_9 + 0.0046309x_{10} + 0.014847\,x_1x_2 + 2.075x_1x_4 + 0.10884\,x_1x_5 + 0.13078\,x_1x_7 + 1.1166\,x_1x_9 - 0.002803\,x_1x_{10} + 0.0090091x_3x_8 + 0.082711x_4x_7 - 0.0041622x_5x_7 + 0.0060324x_5x_8 - 0.0083202\,x_6x_8 + 0.030313x_6x_9 - 0.01704x_7x_9 - 0.00033667x_7x_{10} - 0.013107x_8x_9 + 0.00030857\,x_8x_{10} - 0.085079\,x_4^2 + 0.0041785x_8^2 \quad \text{(A3)}$$

From *

* 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, Deposition, Adhesion/Removal (and loss!)**



Generation
- Lifting mechanism
- Global/local transport
- Other sources/sinks

Deposition
- Gravity
- Turbulence and boundary layer

Adhesion
- Van der Waals forces
- Capillary forces
- Electrostatic forces
- Cementation

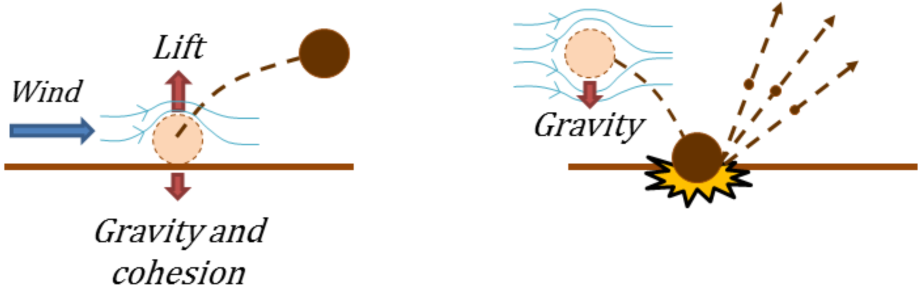
Removal
- Wind
- Gravity
- Rain

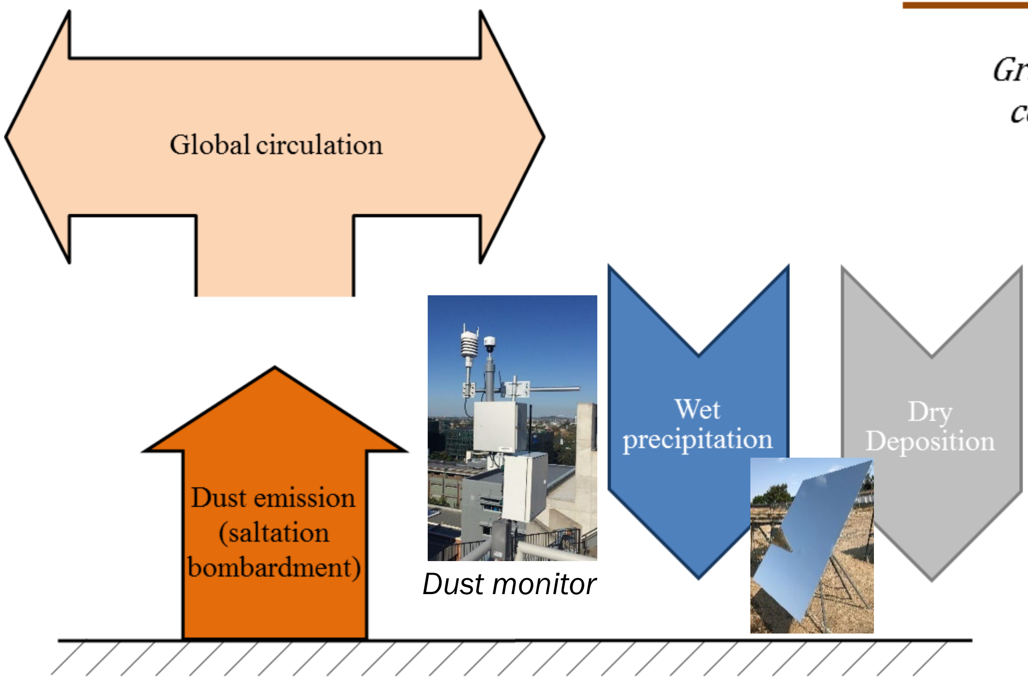
Reflectance Loss
- Shading & Blocking of particle

*Picotti, et al. (2018). Soiling of solar collectors – Modelling approaches for airborne dust and its interactions with surfaces, *Renewable and Sustainable Energy Reviews*

Generation

Lifting, saltation, & transport





Dust monitor

- 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

*Picotti, et al. (2018). Soiling of solar collectors – Modelling approaches for airborne dust and its interactions with surfaces, *Renewable and Sustainable Energy Reviews*

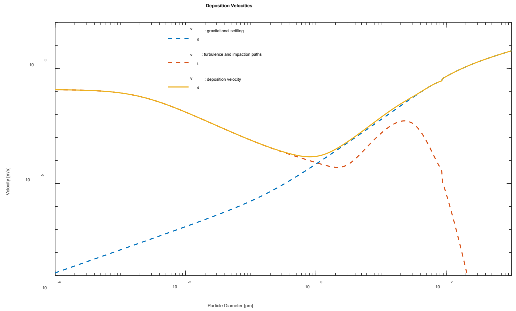
Soiling model overview*,**

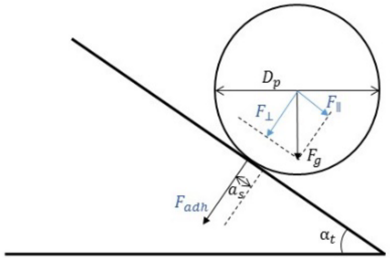
Deposition
- Gravity
- Turbulence and inertia

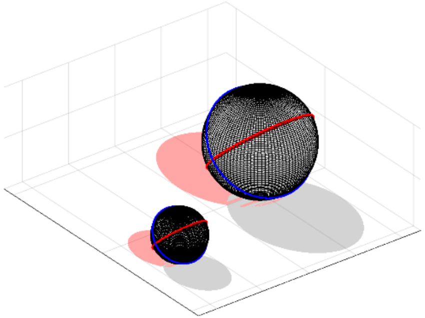
Adhesion
- van der Waals

Removal
- Gravity

Reflectance Loss





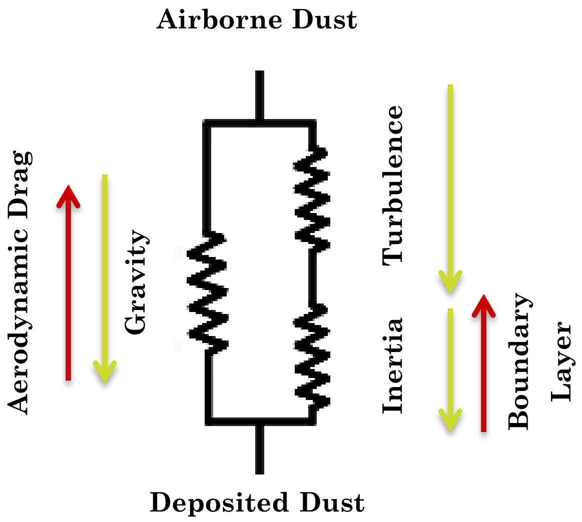


* Picotti, et al. (2018). Soiling of solar collectors – Modelling approaches for airborne dust and its interactions with surfaces, *Renewable and Sustainable Energy Reviews*
** Picotti, et al. (2018). Development and experimental validation of a physical model for the soiling of mirrors for CSP industry applications, *Solar Energy*

Deposition

*The resistance model**

- **Deposition** → Adhesion → Removal → Reflectance Loss



Dust Flux

$$F_t(d) = C_d\, v_d \qquad \left[\frac{\mathrm{kg}}{\mathrm{m}^2\mathrm{s}}\right]$$

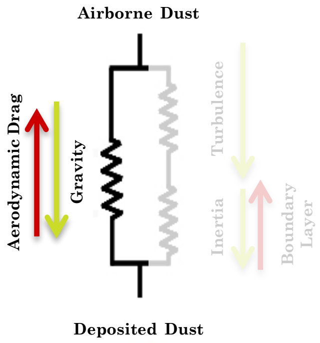
Deposition Velocity

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

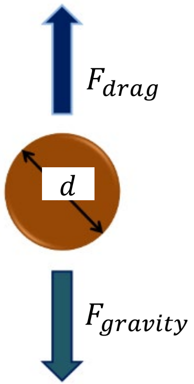
	Units	Description
d	μm	Particle diameter
C_d	$\left[\frac{\mathrm{number}}{\mathrm{m}^3}\right]$	Concentration at diameter d
v_g	$\left[\frac{\mathrm{m}}{\mathrm{s}}\right]$	Gravitational settling velocity (next slide)
r_a	$\left[\frac{s}{m}\right]$	Aerodynamic resistance (in two slides)
r_b	$\left[\frac{s}{m}\right]$	Boundary layer resistance (in two slides)

*Seinfield and Pandis (2016), Atmospheric Chemistry and Physics: From Air Pollution to Climate Change.

Deposition



$$v_d = v_g + \frac{1}{r_a + r_b}$$



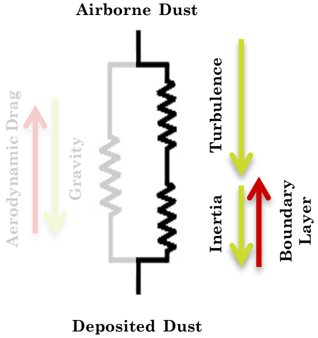
Terminal velocity (from force balance)

$$v_g = \frac{d^2 \rho g \, C_c}{18\mu_a} \qquad Re < 0.1$$

$$v_g = \left(\frac{4 d \rho g C_c}{3 C_D \rho_a}\right)^{0.5} \qquad Re \geq 0.1$$

	Units	Description
ρ	$\frac{\mathrm{kg}}{\mathrm{m}^3}$	Particle density
C_c	$-$	Slip correction factor (for non-continuum effects)
C_D	$-$	Drag coefficient
μ_a	$\frac{N \cdot s}{m^2}$	Dynamic viscosity of air

Deposition



$$v_d = v_g + \frac{1}{r_a + r_b}$$

Aerodynamic resistance

$$r_a = \frac{\ln^2\left(\frac{z}{z_0}\right)}{\kappa U}$$

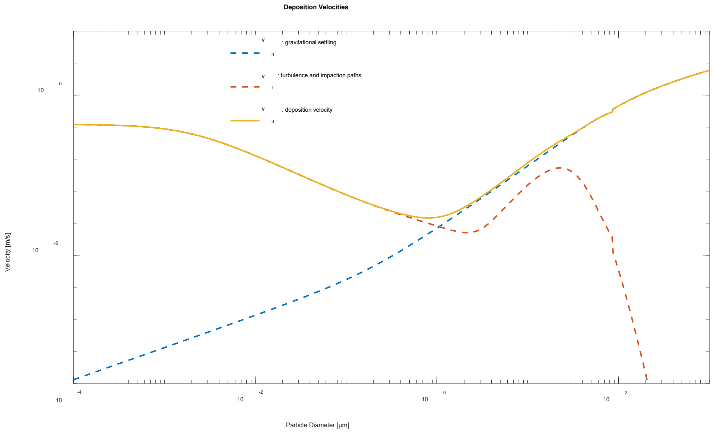
Boundary layer resistance

$$r_b = \frac{1}{u_*(E_{br} + E_{im})\epsilon R_1}$$

$$E_{br} = Sc^{-1/2} \qquad E_{im} = \frac{St^2}{400 + St^2} \qquad R_1 = \exp\left(-St^{1/2}\right)$$

Expressions for r_a and r_b depend on land use / atmospheric conditions

	Units	Description
U	m/s	Wind speed
D	m^2/s	$= \frac{k_b T_t C_c}{3\pi\mu_a d}$ Brownian diffusivity of particles
u_*	m/s	Friction velocity = $\frac{\kappa U}{\ln\left(\frac{z}{z_0}\right)}$
ν_a	m^2/s	Kinematic viscosity of air
Sc	–	Schmidt number = $\frac{\nu_a}{D}$
St	–	Stokes number = $\frac{v_g u_*^2}{\nu_a g}$
κ, k_b	$–, J/K$	von Karman and Boltzman constants

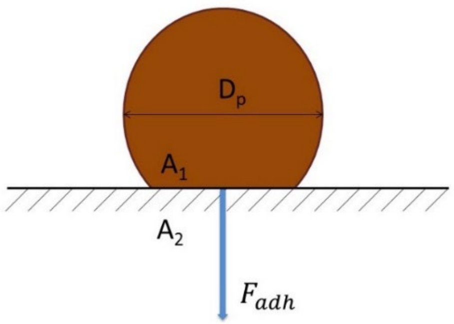


Soiling Model

Adhesion vs gravity moments

Deposition → Adhesion → Removal → Reflectance Loss

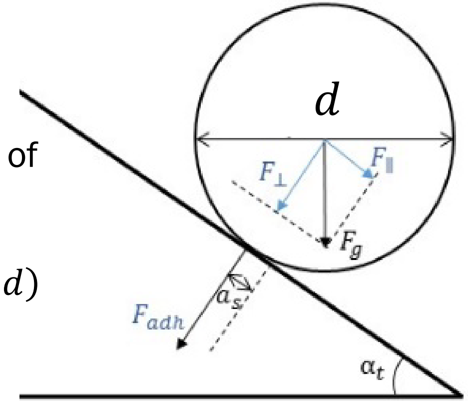
Force of Adhesion (van der Waals)



Dust particles are assumed to be rigid spheres made of Silica

Condition for removal for particle of diameter d:

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



Removal is assumed to be due to gravity-induced rolling

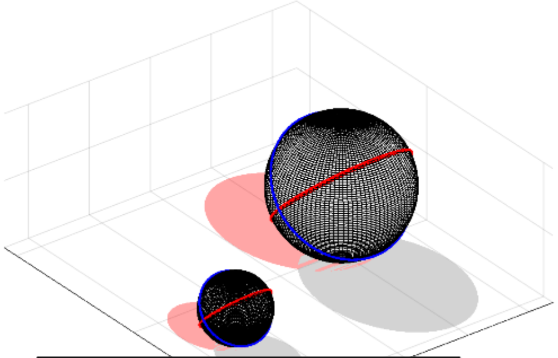
Reflectance Loss

Reflectance is a function of the incidence angle θ

- First surface vs. second surface*,**
- Second surface is more likely for solar mirrors
- Assuming: 1) the reflectance loss is not too high; 2) that θ 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 $\theta = 0$



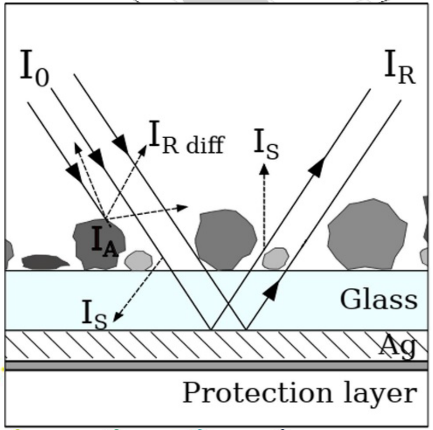


Image from **

* Al-Hasan (1998) "A New Correlation for Direct Beam Solar Radiation Received by Photovoltaic Panel with Sand Dust Accumulated on Its Surface."
** Bellmann et al. (2020), "Comparative Modeling of Optical Soiling Losses for CSP and PV Energy Systems."

Soiling Model

Putting it all together

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

$$F_t(d, U_t, T_t) = \color{red}{\boldsymbol{C_t(d)}} \cdot v_d \cdot \cos(\alpha_t)$$

$n_t(d) = \int_{t_0}^{t} F_\tau(d, U_t, T_t) d\tau$ (number dist. on mirror)

Deposition

$$d_c = \min d$$

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

$$m_t(d \geq d_c) = 0$$

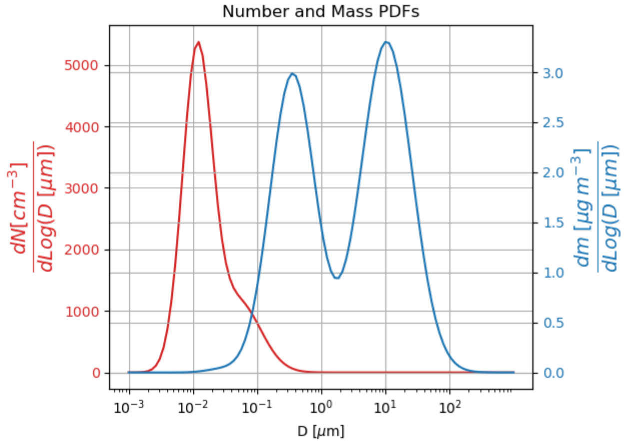
Adhesion/Removal

$$A_{soil,t} = \frac{\pi}{4} \int_0^{\mathrm{d}_c} \delta^2 \cdot n_t(\delta)\ d\delta$$

$$A_{soil,t} \approx \frac{2A_{soil,t}}{cos(\theta_t)}$$

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

Reflectance Loss



Assumed dust distribution to convert from single measurement → $\color{red}{C_t(d)}$

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: $\left(U_k, T_k, PM_{x,k}\right)\ k = 1,2,\dots,K$
- Measure dust concentration $PM_{x,k}$ (This is TSP if $x \to \infty$)
- Average tilts over each interval,α_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)

$$\mu(U_k, T_k; hrz0) = \frac{\pi}{4}\int_0^{\mathrm{d}_c} D^2 \cdot v_d\left(D, U_k, T_k\right) \cdot \hat{n}(D) dD$$

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) $k = 1,2,\dots,K$
- Measure dust concentration $PM_{x,k}$ (This is TSP if $x \to \infty$)
- Average tilts over each interval,α_i
- 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)

$$\hat{A}_{soil,k} \approx \sum_{i=0}^{k-1} \frac{PM_{x,i}}{\overline{PM}_x} \cdot cos(\alpha_i) \cdot \mu(U_i, T_i; hrz0)$$

Cumulative area loss since t_0

$$\hat{\rho}_k = \rho_0 \left(1 - \frac{2\hat{A}_{soil,k}}{cos(\theta_k)\, A_{mirror}}\right)$$

Reflectance at incidence angle θ_k

Recent developments: a stochastic loss model

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

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

where $\varepsilon_i \sim \mathcal{N}\left(0, \sigma_{dep}^2\right)$ are independent noise terms. This model has two parameters: $hrz0$ and σ_{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 $\epsilon_{k_i} \sim \mathcal{N}\left(0, \sigma_{m,k_i}^2\right)$ 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_{k_i} $i = 1,2, \ldots, N$ available

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

Deterministic model (least squares)

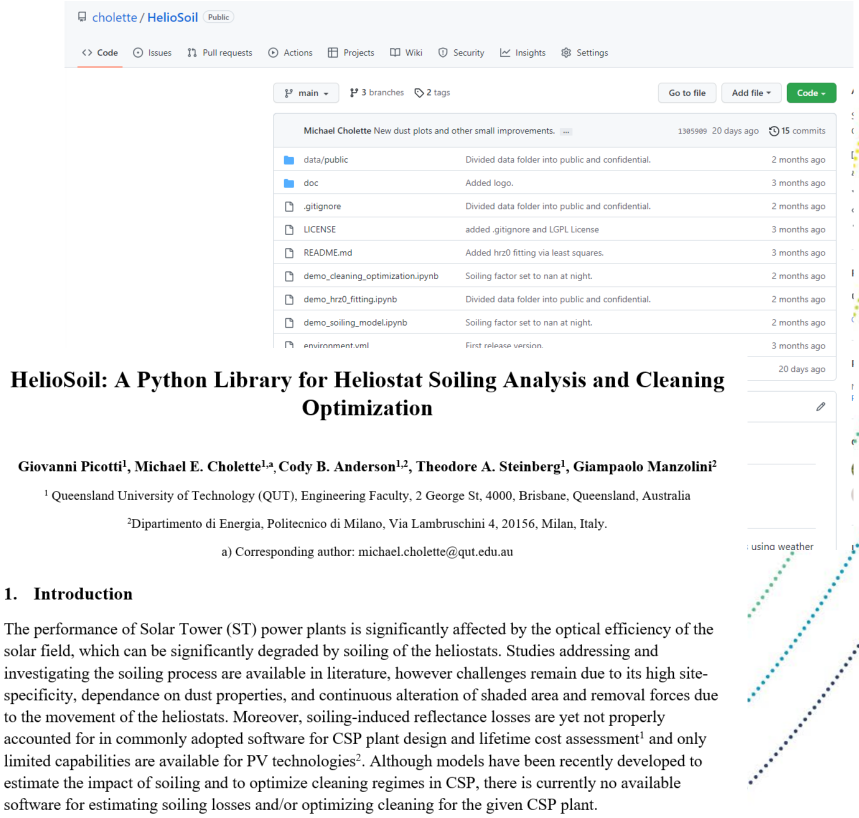
$$\widehat{hrz0}, \hat{\sigma}_{dep} = \arg\max_{h>1} \sum_{i=1}^{N} \log p\left(r_{k_i} - r_{k_{i-1}} \middle| h, \sigma_{dep}^2\right)$$

Stochastic Model (maximum likelihood)

where $p\left(r_{k_i} - r_{k_{i-1}} \middle| h, \sigma_{dep}^2\right)$ 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



HelioSoil: A Python Library for Heliostat Soiling Analysis and Cleaning Optimization

Giovanni Picotti[1], Michael E. Cholette[1,a], Cody B. Anderson[1,2], Theodore A. Steinberg[1], Giampaolo Manzolini[2]

[1] Queensland University of Technology (QUT), Engineering Faculty, 2 George St, 4000, Brisbane, Queensland, Australia

[2]Dipartimento di Energia, Politecnico di Milano, Via Lambruschini 4, 20156, Milan, Italy.

a) Corresponding author: michael.cholette@qut.edu.au

1. Introduction

The performance of Solar Tower (ST) power plants is significantly affected by the optical efficiency of the solar field, which can be significantly degraded by soiling of the heliostats. Studies addressing and investigating the soiling process are available in literature, however challenges remain due to its high site-specificity, dependance on dust properties, and continuous alteration of shaded area and removal forces due to the movement of the heliostats. Moreover, soiling-induced reflectance losses are yet not properly accounted for in commonly adopted software for CSP plant design and lifetime cost assessment[1] and only limited capabilities are available for PV technologies[2]. Although models have been recently developed to estimate the impact of soiling and to optimize cleaning regimes in CSP, there is currently no available software for estimating soiling losses and/or optimizing cleaning for the given CSP plant.

Experimental activity & model prediction assessment

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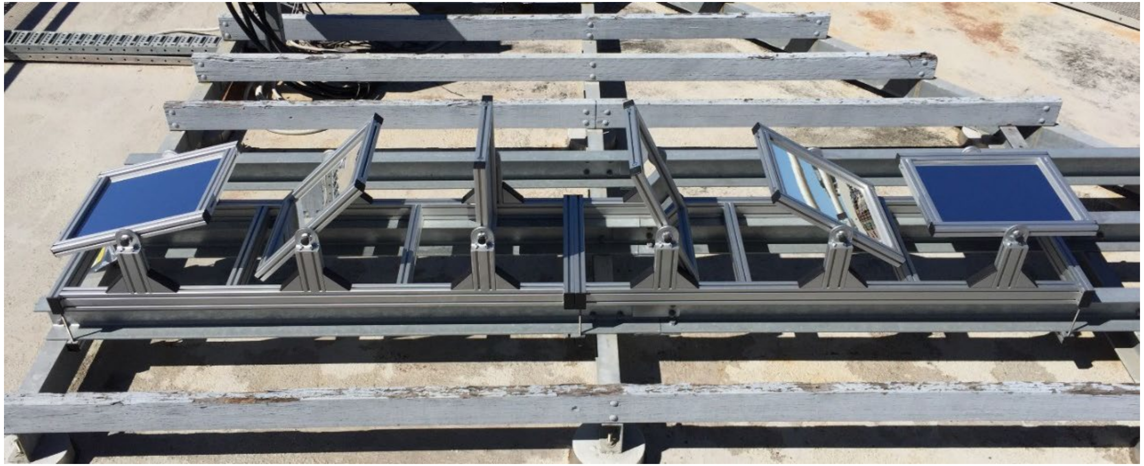
Australian Solar Thermal Research Institute

Soiling Rig #1 — QUT

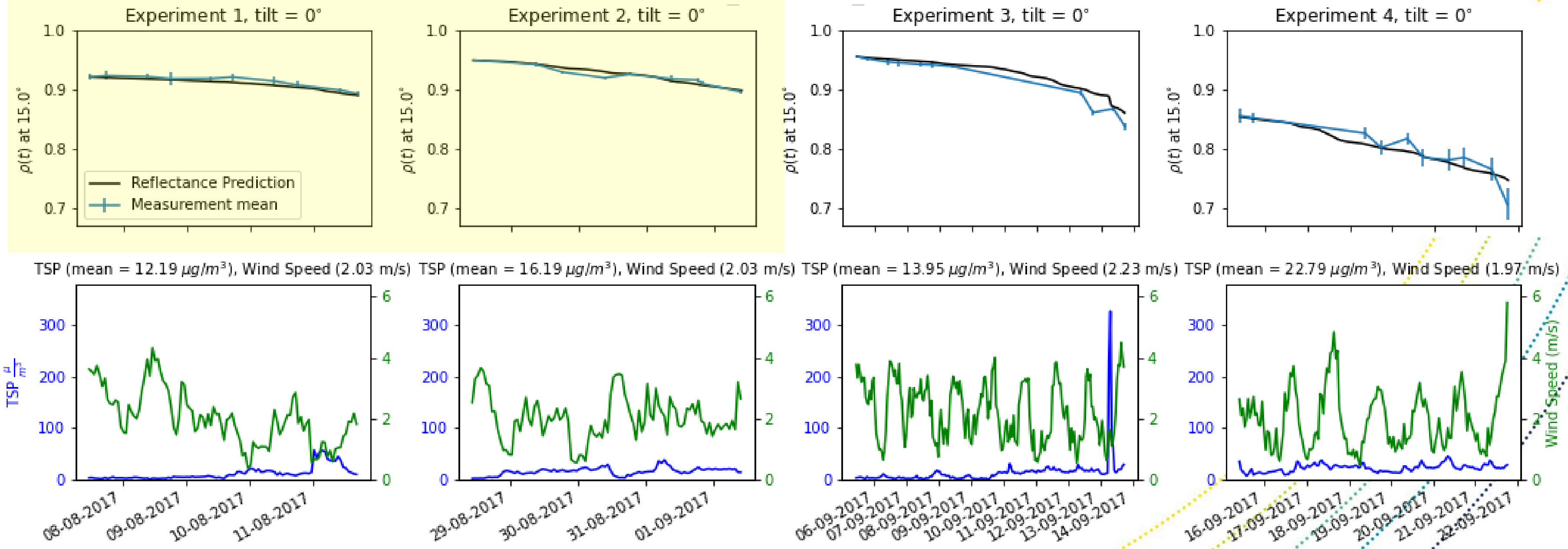
Acceptance Angle:	4.6-46 mrad
Wavelength:	0.4-0.8 μm
Incidence Angle:	15°
Repeatability:	± 0.2%



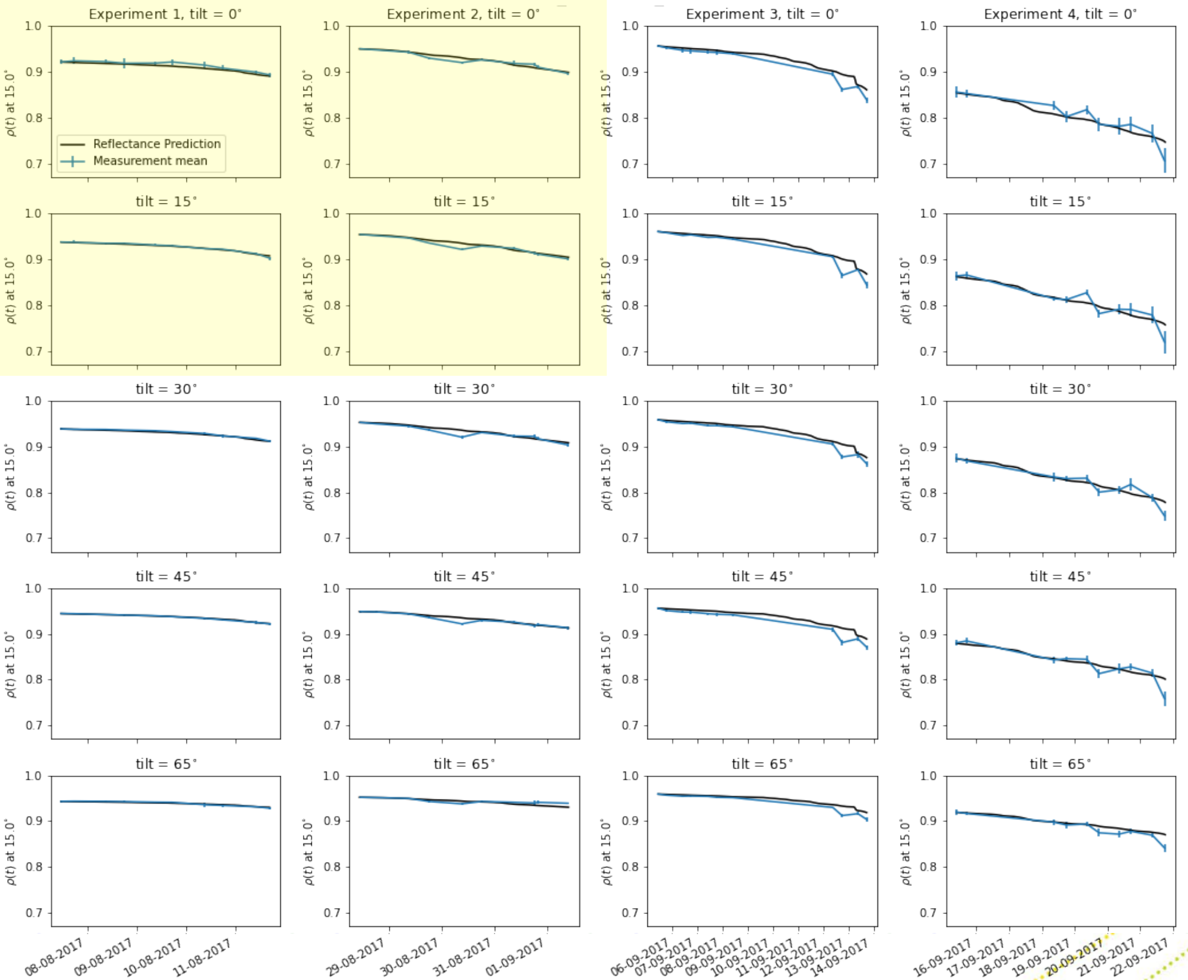
Performance of the model on QUT data

Different degradation rates due to different wind/airborne dust

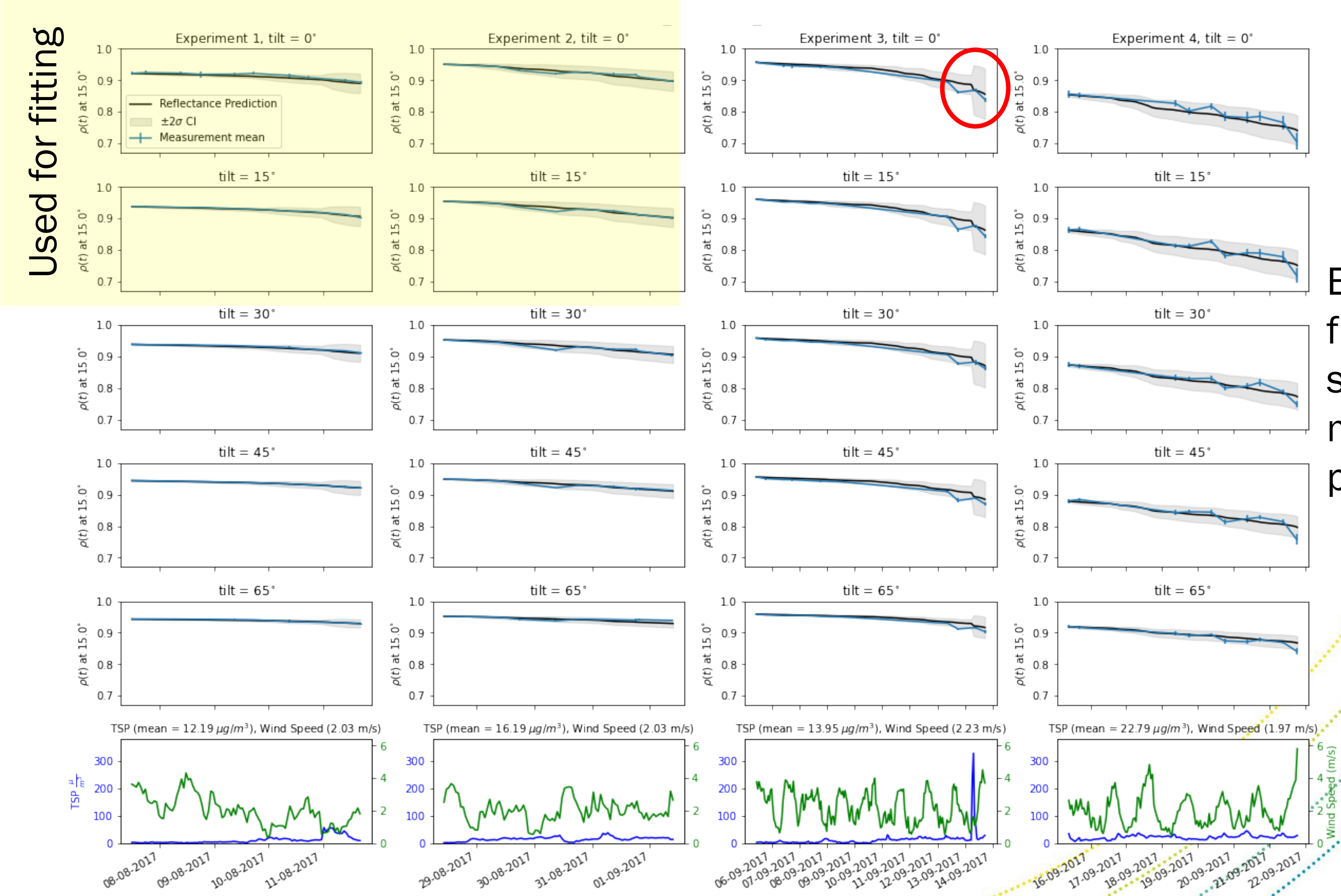
Used for fitting



Used for fitting



Prediction of tilt effects is quite good



Early results from stochastic model are promising

Soiling Rig #2 — Mount Isa, Queensland

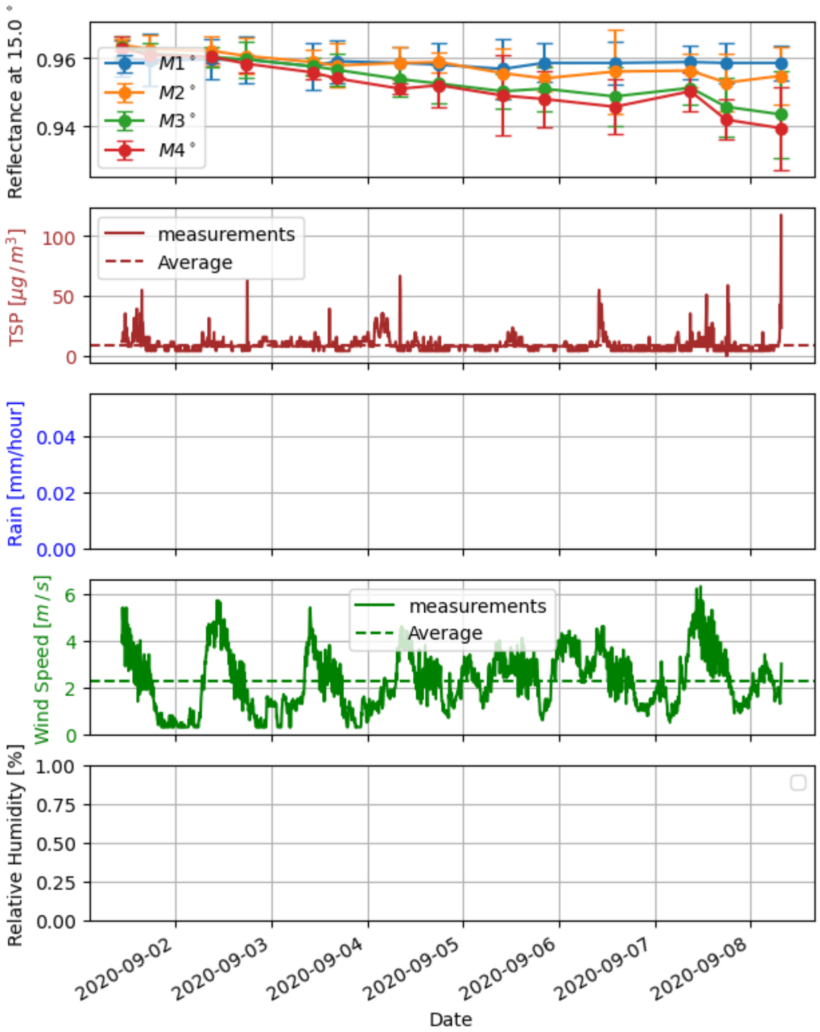
- Installation of dust and weather monitoring station
- Deployment of mirror test rig with 18 differently tilted and oriented samples
- Measurements taken with a D&S reflectometer twice a day for one week

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

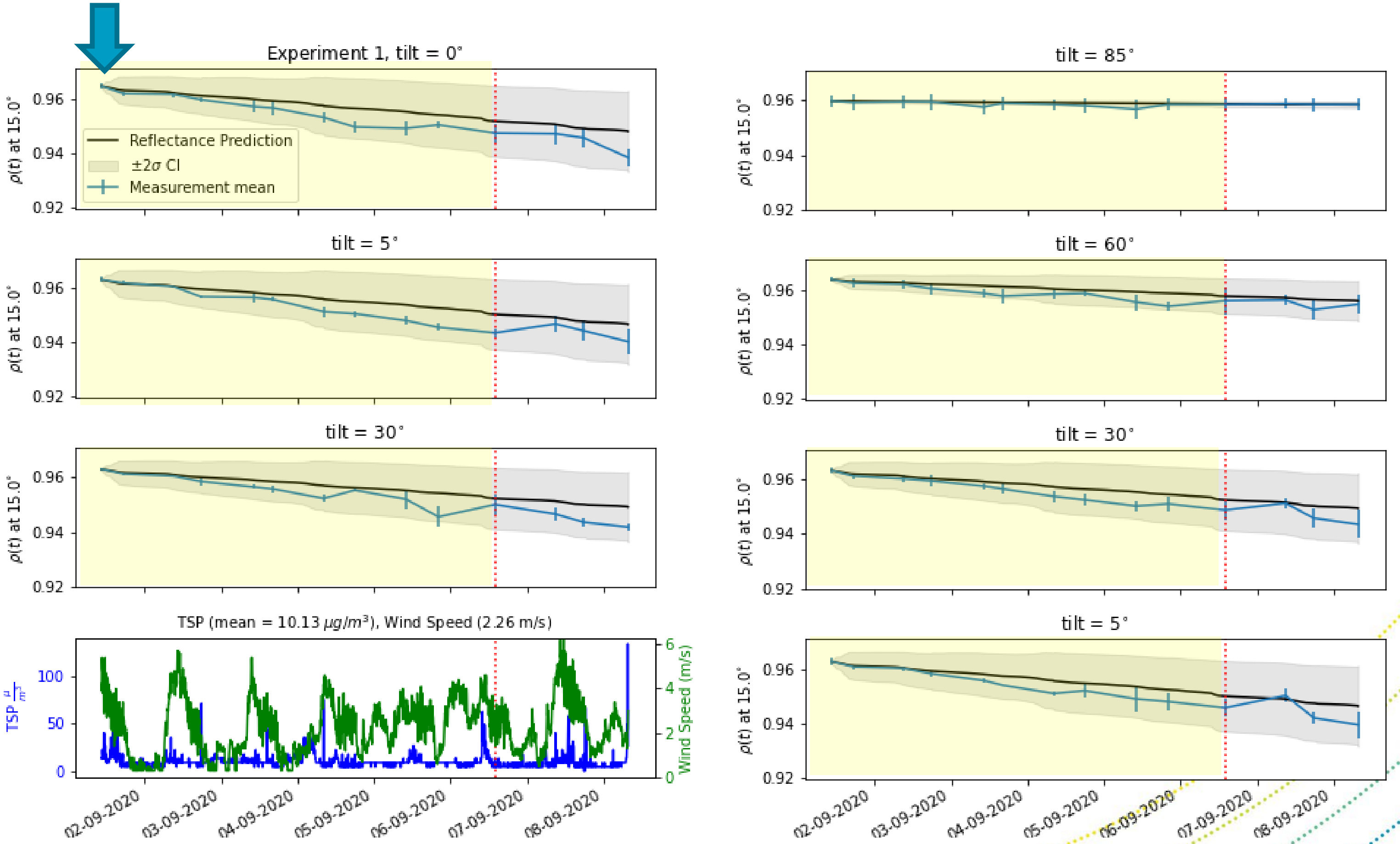
Example Data

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



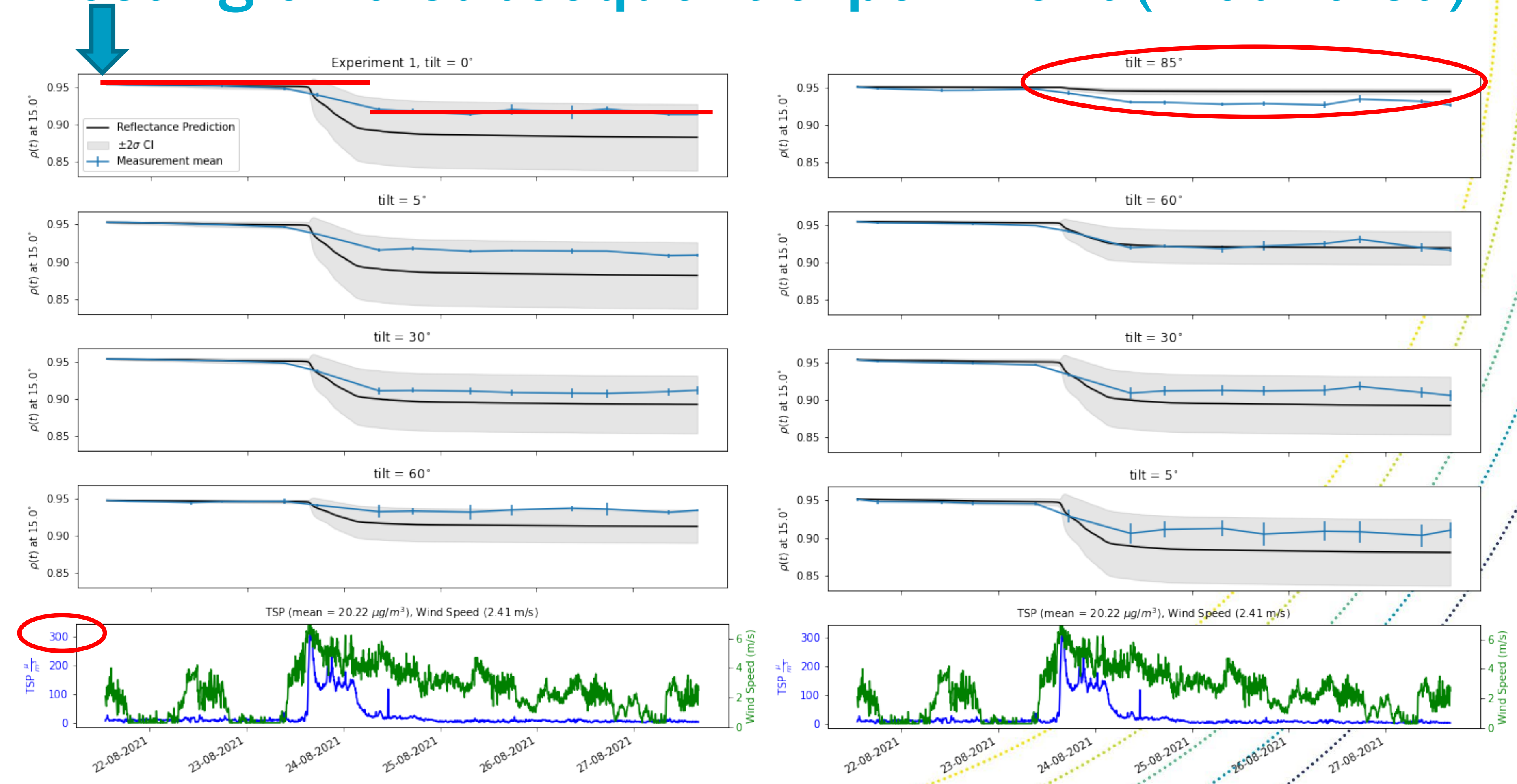
Performance of model in Mount Isa



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)



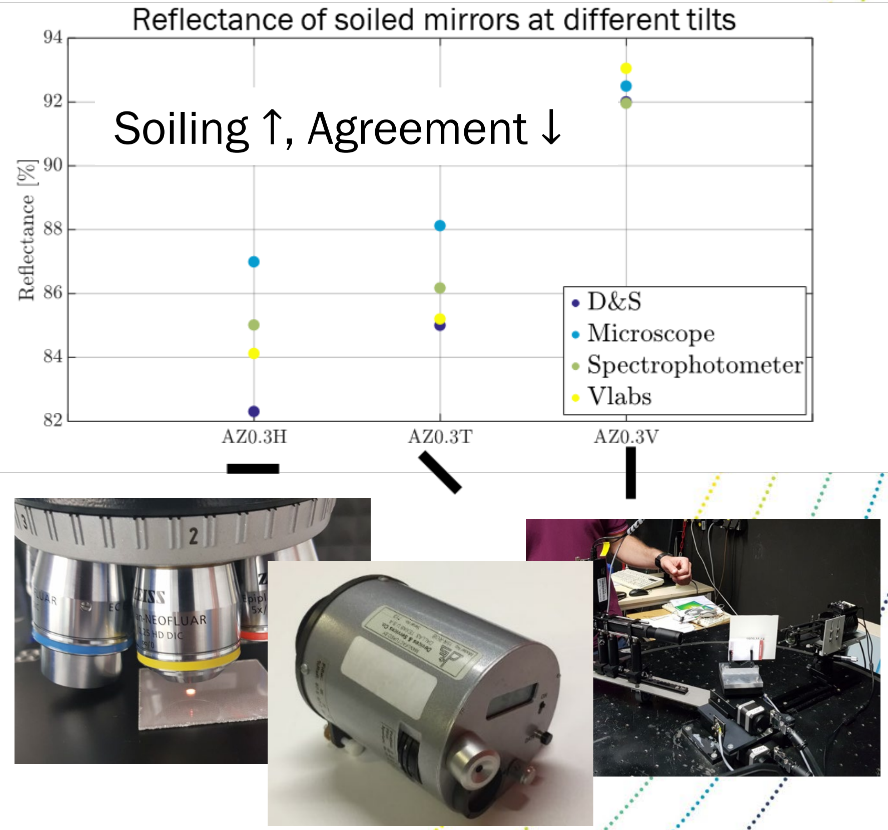
Soiling Rig #3 — Wodonga, Victoria

- Dust sampler measures five different PM_x fractions

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

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)



* Picotti, et al. (2021). Evaluation of reflectance measurement techniques for artificially soiled solar reflectors: Experimental campaign and model assessment, *Solar Energy Materials and Solar Cells*

Cleaning optimization

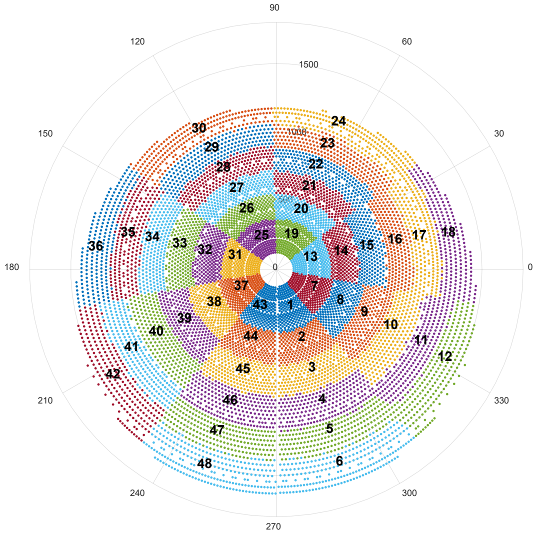
ASTRI

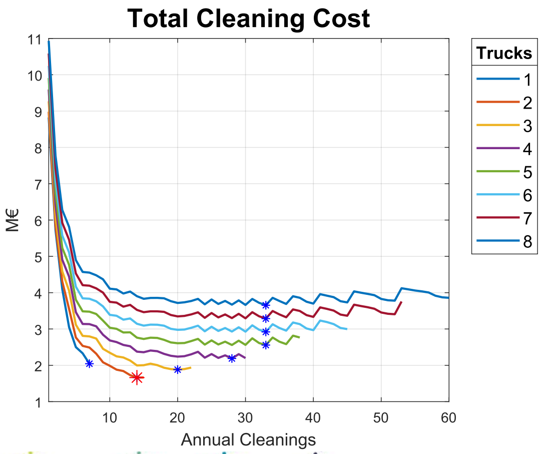
Australian Solar Thermal Research Institute

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:*

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

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

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

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

Cleaning optimization

Total cleaning costs

Optimal cleaning minimized the *total cleaning cost:*

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

Cleaning optimization

Total cleaning costs

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

Area of sector j and DNI at time interval i

Cleaning optimization

Total cleaning costs

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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.

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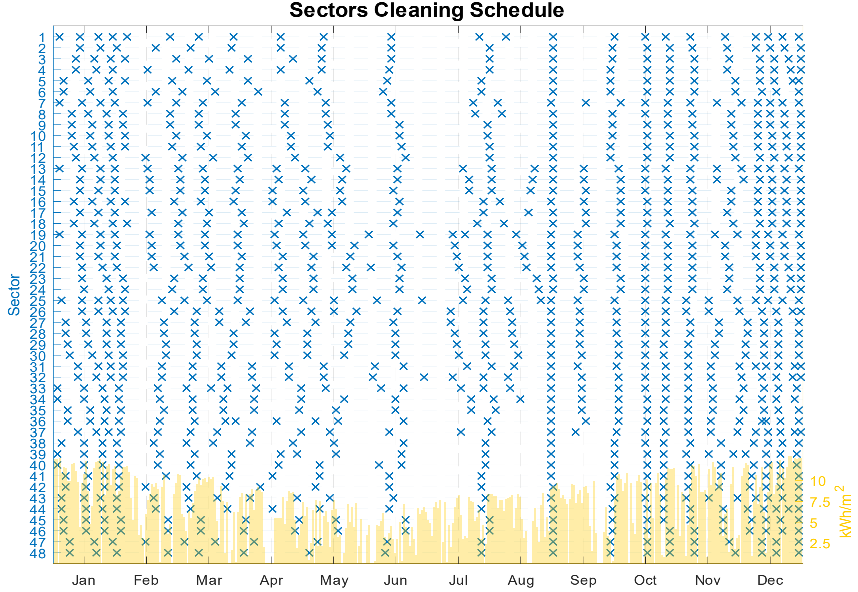
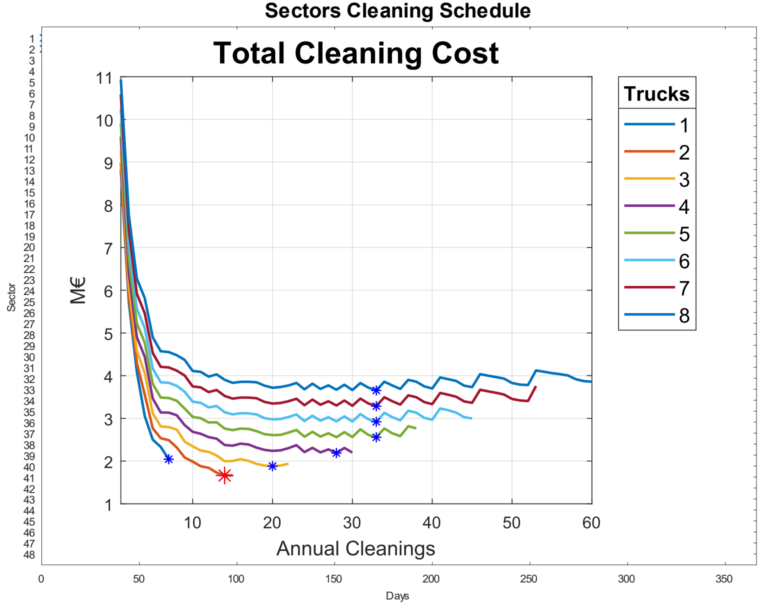
Price of electricity

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$



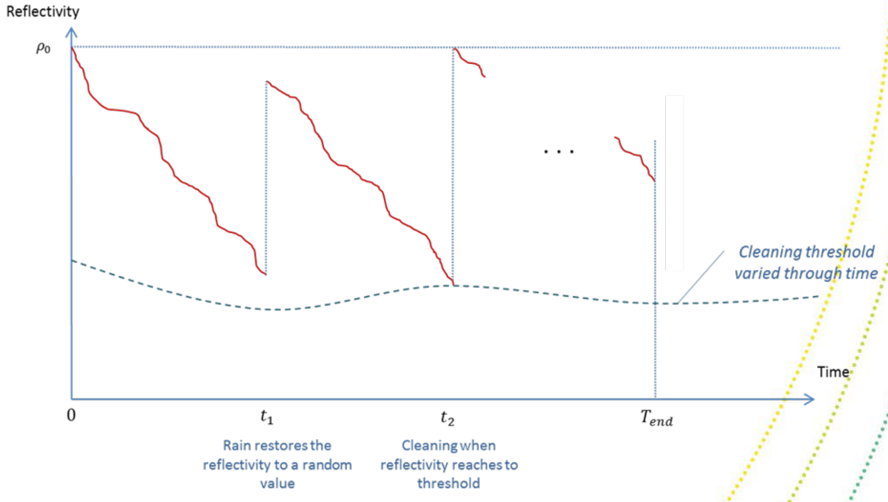
MILP provides "perfect knowledge" solution as a benchmark (not implementable)
Heuristic is close and is implementable without knowledge of future soiling

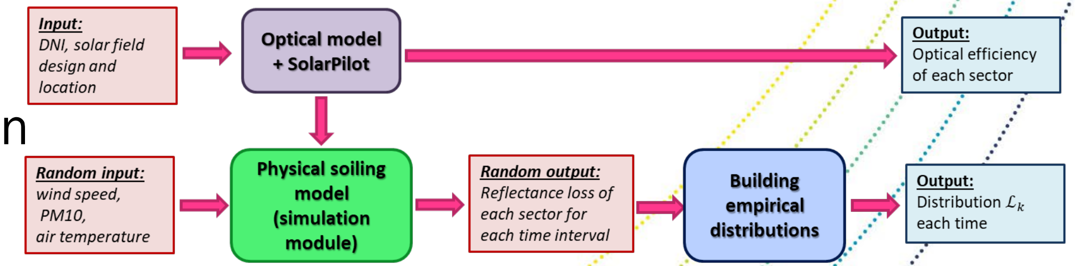
* Picotti, et al. (2020). Optimization of cleaning strategies for heliostat fields in solar tower plants, *Solar Energy*

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.



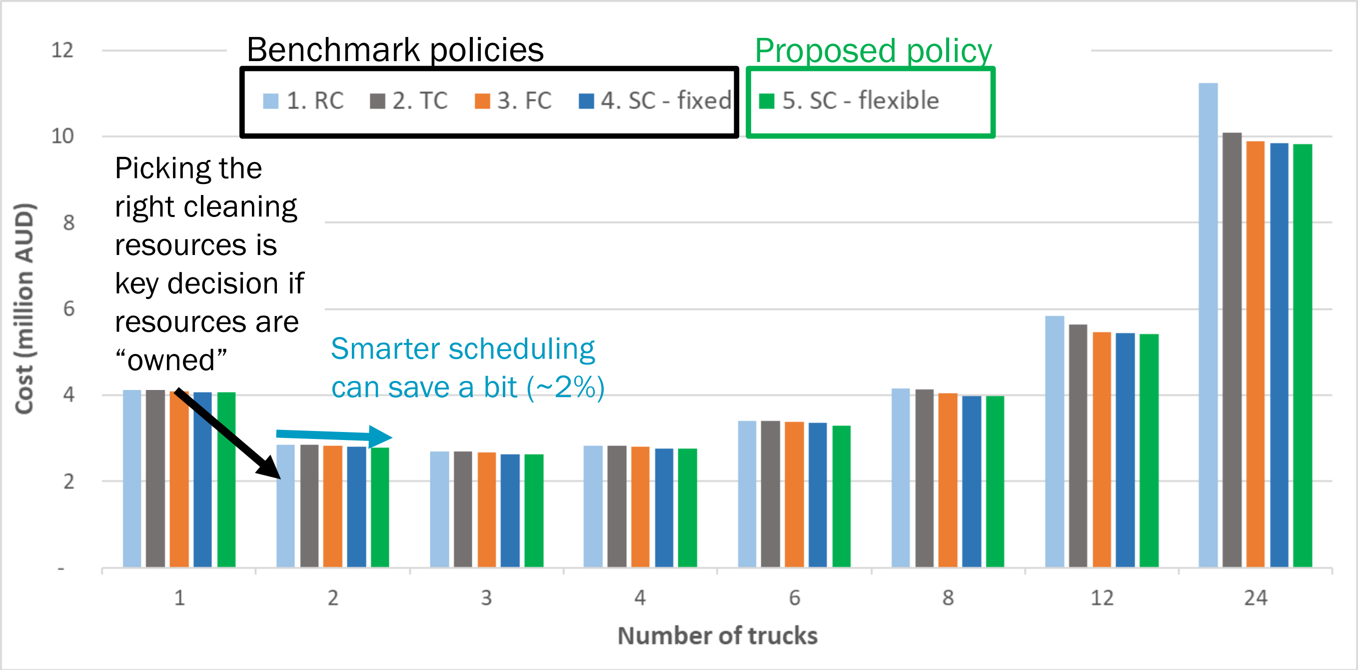


* Truong Ba, et al. (2017). Optimal condition-based cleaning of solar power collectors, *Solar Energy*

** Truong-Ba, et al. (2020). Sectorial reflectance-based cleaning policy of heliostats for Solar Tower power plants, *Renewable Energy*

Cleaning Optimization

Reflectance Based[*, **]



* Truong Ba, et al. (2017). Optimal condition-based cleaning of solar power collectors, *Solar Energy*

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HelioCon Soiling Subtask

U.S. Department of Energy
HelioCon
Heliostat Consortium for
Concentrating Solar-Thermal Power

ASTRI
Australian Solar Thermal
Research Institute

Soiling subtask

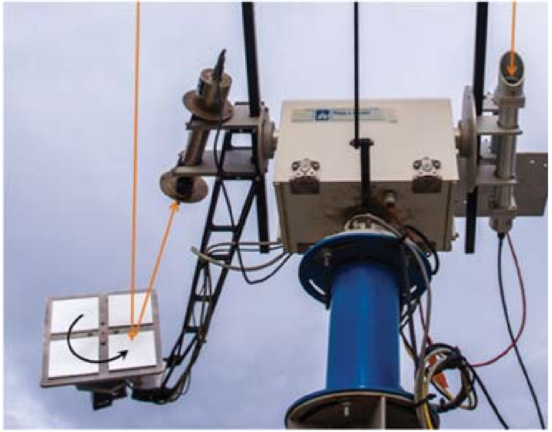
Scope

- 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



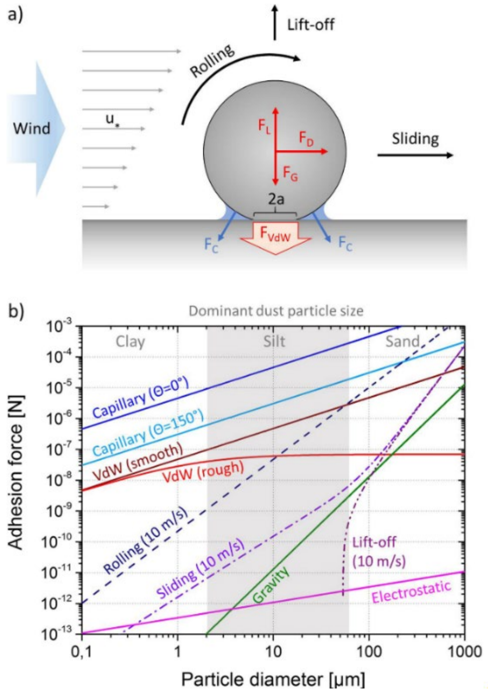
(A) TraCS (TraCS4 variant shown)

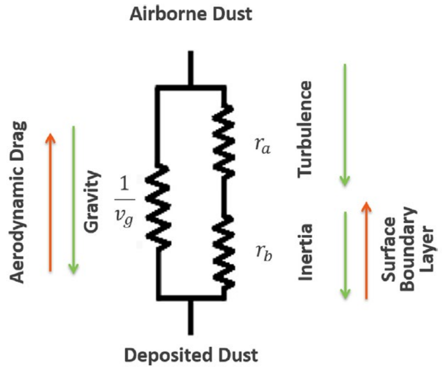
(B) AVUS

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)



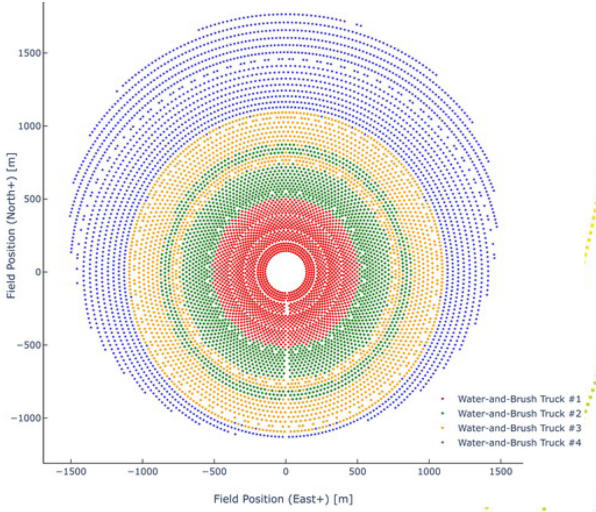


From: Ilse et al. (2018) Fundamentals of soiling processes on photovoltaic modules, *Renewable and Sustainable Energy Reviews*

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

https://helioscsp.com/tag/cleaning-systems-for-heliostats/

Soiling subtask

Top gaps

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

Conceptual Design	Components	Integrated Heliostat	Mass Production	Deployed Field
So5: Soiling evaluation at site selection So15: Trade-offs between soiling losses, cleaning regime, design choices (e.g., site selection, solar multiple), and heliostat reliability are poorly understood	So14: No standard or data to assess anti-soiling coating durability/performance			So13: Design and automation of new cleaning systems is underexplored

Conclusions

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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-hIf4qxuAbHUHK-xgZK
- Slides available here: https://drive.google.com/drive/folders/1162LN82ImgurpCODnJDLKsERCWo-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