Optimization of cleaning strategies for heliostat fields in solar tower plants

Giovanni Picotti[1,2*], Luca Moretti[2], Michael E. Cholette[1], Marco Binotti[2], Riccardo Simonetti[2], Emanuele Martelli[2], Ted Steinberg[1], Giampaolo Manzolini[2]

[1]*Queensland University of Technology, 2 George St, 4000, Brisbane, QLD, Australia*
[2]*Dipartimento di Energia, Politecnico di Milano, via Lambruschini 4A, 20156, Milan, Italy*

[*] Corresponding author: email g.picotti@qut.edu.au ; phone +61 07 3138 0328.

Abstract

The reduction due to soiling of the optical efficiency of the heliostats in the solar field is a significant detrimental factor in concentrating solar power (CSP) plants. Artificial cleaning is required to maintain acceptable values of optical efficiency, especially in those areas where CSP tends to be economically viable, i.e. where the yearly available DNI is high and rain is scarce. The optimization of the cleaning activities is then a fundamental step to properly balance the operation and maintenance (O&M) costs of the plant with the revenue losses due to soiled heliostats. In this work the best cleaning schedule for a given solar field is computed through a mixed integer linear programming (MILP) model and compared with the results of a heuristic approach. The optical efficiency reduction is assessed for each sector of the solar field through a physical model. The MILP model accounts for the soiling impact and finds the most economical solution in terms of cleaning trucks number and number of cleanings. The optimal cleaning schedule for each sector of the solar field is obtained by minimizing the total cleaning cost (TCC), which is the sum of direct cleaning costs and monetized losses due to soiling. A few test cases are evaluated to demonstrate the strength and the applicability of the developed algorithm. The TCC improvements span between 0.7% and 19.6%, depending on the different scenarios and cost structures considered. For the case studies considered, the savings due to the MILP optimized cleaning strategy were between 927 kAU$/yr and 4744 kAU$/yr (575 k€/yr and 2941 k€/yr).

Keywords: Heliostat cleaning optimization; total cleaning cost minimization; solar tower plant; mixed integer linear programming; operation and maintenance optimization.

Published Journal Article available at: https://doi.org/10.1016/j.solener.2020.04.032

Nomenclature

A_j	Area of one sector
A_{hel}	Heliostat area [m^2]
A_{soil}	Soiling area [m^2]
C_{call}	Call cleaning cost [$/call]
C_{cl}	Cleaning cost [$/y]
$C_{cl,fix}$	Fixed cleaning cost [$/truck]
$C_{cl,rent}$	Rent cleaning cost [$/cleaning]
$C_{cl,var}$	Variable cleaning cost [$/cleaning]
C_d	Airborne dust concentration [μg/m^3]
C_{deg}	Degradation cost [$/y]
$C_{o\&m}$	Operation and maintenance cost (except cleaning) [$/MWh]
CSP	Concentrating Solar Power
d_{cl}	Cleaning interval [days]
DNI	Direct Normal Irradiation [kWh/m^2]
f_{soil}	Soiling factor
$\tilde{f}_{s,\ell,t}$	Soiling factor scheduling variable
F_d	Flux of Dust [μg/m^2/s]
HP	High Price
HTF	Heat Transfer Fluid
LCOE	Levelized Cost of Electricity [$/MWh]
LP	Low Price
MILP	Mixed Integer Linear Programming
n_{cl}	Number of cleanings
n_{call}	Number of calls
n_{tr}	Number of trucks
O&M	Operation and Maintenance
P_{el}	Electricity selling price [$/MWh]
PM	Particulate Matter
PV	Photovoltaic
Q_{rec}	Thermal power available at the receiver [MW]
Q_{loss}	Thermal losses at the receiver [MW]
SA	South Australia
ST	Solar Tower
TCC	Total Cleaning Cost [$]
TP	Total Profit [$]
UAE	United Arab Emirates
v_d	Deposition velocity [m/s]
$z_{s,l,t}$	Binary cleaning scheduling variable
α_{tilt}	Tilt angle
η_{opt}	Optical efficiency
$\eta_{opt,clean}$	Nominal optical efficiency
η_{pb}	Power block efficiency
η_{th}	Receiver thermal efficiency

1 Introduction

The exploitation of renewable and sustainable energy sources is one of the most important challenges the world must face in the coming decades. Among the available technologies, Concentrating Solar Power (CSP) plants have the capacity to provide reliable and stable power during extended periods due to the implementation of low cost thermal energy storage. CSP plants harvest solar radiation through large reflecting surfaces that focus the collected power towards a receiver. Among the different CSP technologies, Solar Tower (ST) plants consist of thousands of heliostats reflecting the solar beams towards a central receiver, usually deployed at the top of a tall tower. The optical efficiency of the heliostats must be as high as possible to maximize the solar radiation harvesting. A strongly detrimental factor that influences the optical efficiency is the soiling of the heliostats, which significantly reduces their reflectance (Kutscher et al., 2010). Lower optical efficiency results in lower electricity production, as the available collected power on the receiver is reduced, affecting the economic profitability of the ST plant. The negative effect of heliostat soiling is primarily addressed through the cleaning of the heliostats (Sarver et al., 2013). According to previous studies (Kutscher et al., 2010), the cost of heliostat cleaning activities accounts for about 20% of the Operation and Maintenance (O&M) costs related to the solar field, which in turn account for a 25% share of the total O&M costs for a CSP plant. Therefore, since the total O&M costs (including personnel and consumables) are ~14-17% of the Levelized Cost of Electricity (IRENA and IEA-ETSAP, 2013; IRENA Secreteriat et al., 2012), applying efficient cleaning strategies can potentially reduce the Levelized Cost of Electricity (LCOE) by 1%, without any technology variation nor component replacement. The definition of optimal cleaning strategies thus provides an important opportunity to reduce the LCOE for ST plants (Pfahl et al., 2017).

In literature, there are several works dealing with the optimization of the heliostat field layout (Sanchez and Romero, 2006), both based on energy analysis (Ortigosa et al., 2018) and techno-economic assessment (Larrayoz et al., 2019). Similarly, there is large interest in the development of innovative heliostats (Pfahl et al., 2017) as well as proposing different aiming strategies (Salomé et al., 2013) based on both heuristic approaches (Sánchez-González and Santana, 2015) and deterministic ones (Astolfi et al., 2016) to optimize the solar flux distribution on the receiver. Fewer studies dealt with the specific issue of the optimal heliostat cleaning schedules, although various methods have been developed (Fernández-García et al., 2014). Some studies regarding PV technologies dealt with the optimization of cleaning operations: through the identification of an average soiling threshold (Fathi et al., 2017), expected power generation threshold based on soiling level and environmental condition (Wang and Xu, 2018), or a rigorous mathematical calculation assuming soiling production losses to vary as a decreasing exponential function (Jones et al., 2016). Other studies targeting parabolic trough technologies also considered the issue of identifying the best cleaning frequency: among the first, at Sandia National Laboratories, Bergeron and Freese (1981) assessed the optimal cleaning frequency based on a constant soling rate and a predicted daily direct solar energy availability. More recently, Wolferstetter et al. (2018) realized a study considering a time-dependent soiling rate throughout the year to identify the most suitable cleaning strategy. Although using experimental data to assess the reduced optical efficiency of the solar collectors, a homogeneous soling rate was applied on the whole solar field, and the cleaning order of the loops was always kept the same. In a follow-up work, while preserving the assumption of uniform soiling rate for each solar field loop, Terhag et al. (2019) developed a cleaning strategy optimization based on reinforcement learning, using an enlarged synthetic dataset of soiling rate measurements collected at the Plataforma Solar de Almeria in Spain over five years.

In the authors' previous work (Picotti et al., 2019), the impact of different cleaning frequency on the average solar field optical efficiency was assessed for one month of simulation, considering only direct operational cleaning costs (i.e. no trucks, personnel). Depending on thechosen cleaning frequency, a fixed percentage of the solar field area was cleaned each day following a pre-defined order, without investigating the impact of the chosen order.

Although there have been several studies on heliostat soiling and cleaning approaches, only two published papers deal with the optimization of heliostat cleaning strategies. Truong Ba et al. (2017) proposed a condition-based cleaning policy based on a finite Markov Decision Process which sought to minimize the total cleaning cost, i.e. the sum of revenue loss due to soiling and direct cleaning costs. The proposed cleaning strategy was applied to an Australian case study and saved between 5 and 30% of total cleaning costs compared with a fixed-time strategy. However, the methodology requires measurement of the field-averaged reflectance and the optimization assumes that the field can be cleaned in a single day, which is not realistic for large-scale CSP plants. In another study, Ashley et al. (2019) developed a cleaning procedure based on a heliostat clustering and integer programming to maximize the energy collected. A heuristic method was subsequently used to refine the solution to minimize the overall cleaning route length among all the clusters. The proposed methodology resulted in an energy increase of 5% when compared to a simple baseline schedule. Yet, the study uses a time- and space-constant soiling losses across the field and did not consider the economics, i.e. the balance of the cost of cleaning activities and revenue. Thus, the provisioning of cleaning resources (e.g. trucks, personnel) was not optimized.

In this paper, new cleaning strategies are developed to optimize the heliostats cleaning schedule. Starting from a physical model of the soiling process (Picotti et al., 2018, 2017) and measured environmental parameters (i.e. airborne dust concentration, wind speed, air temperature, DNI), the (inhomogeneous) soiling losses are predicted across the solar field. Based on these predictions and on the technical capabilities of the available cleaning resources, the sum of revenue loss due to soiling and direct cleaning costs is minimized, identifying both the optimal provisioning of cleaning resources and the optimal cleaning schedule of different sectors of the solar field.

With respect to previous studies, the present work has two major contributions. Firstly, the optimization is conducted using soiling predictions based on a physical model that considers local conditions and inhomogeneous soling across the solar field, as opposed to the uniform or averaged efficiency losses assumed in previous studies. Secondly, the optimal cleaning schedule is determined considering the economics of cleaning activities under resource limitations, which enables the optimization of the cleaning resource provisioning that was neglected in earlier studies.

Two different strategies are developed in this study: a mixed-integer linear program (MILP) and a simplified heuristic. In either case, the result of the cleaning strategy is the identification of the optimal number of sectors to be cleaned each day (i.e. the number of trucks to be deployed) and the cleaning order of the different sectors. The proposed cleaning strategies were numerically tested on two 100MW ST plants located in two different geographical areas with different environmental conditions. The analyses are performed on yearly basis, to assess the potential of the approach and point out differences in the cleaning strategies. The currency used in the economic analysis across the whole paper, unless specifically indicated, is the Australian Dollar (1AUD = 0.62EUR)[1].

The paper is organized as follows: Section 2 presents the solar field optical efficiency model considered in the optimization function focusing on the sectorial division and the soiling rate assessment. Section 3 discusses the heuristic and deterministic optimization approaches adopted. Section 4 describes the case studies selected for the analysis and results are reported and analysed in Section 5. Finally, the last section draws some general conclusions on the different approaches pointing out some possibilities for future studies.

[1] Conversion rate on 06.09.19

2 Sectorial optical efficiency assessment

The cleaning strategy optimization requires the evaluation of the optical efficiency of the different heliostats, depending on their relative position in the solar field. The optical efficiency is computed as the product of two main terms: the optical efficiency of clean heliostats $\eta_{opt,clean}$ and the soiling factor f_{soil}. It must be stressed that both terms are time-dependant and change for each heliostat, depending on its relative position and tracking motion. Therefore, both the optical efficiency in clean conditions and the soiling factor must be computed on a relatively short time basis (hourly in this work) for the entire year so that:

$$\eta_{opt_h} = \eta_{opt,clean_h} \cdot f_{soil_h} \quad (1)$$

To reduce the computational time required for the assessment of the optical efficiency of each heliostat, the solar field is divided into sectors with an equal number of heliostats. Each sector is characterized by a representative heliostat that is located in its geometrical barycentre. The number of sectors depends on the solar field size and cleaning speed in terms of square meters of heliostats per hour, which eventually determines the number of angular and radial partitions of the solar field. Further considerations could be required if also considering the computational time and capacity. The soiling model used in this work to compute the soiling factor was discussed in previous publications (Picotti et al., 2019, 2018) and only the main outcomes of these studies are described in this paper for brevity.

The amount F_d of dust that falls on the heliostats is calculated from the airborne dust concentration C_d, which is considered uniform over the entire solar field, the deposition velocity v_d, and the tilt angle α_{tilt} as (Picotti et al., 2019, 2018):

$$F_d = C_d \cdot v_d \cdot \cos(\alpha_{tilt}) \quad (2)$$

The tilt angle must be computed for each time step since it depends on both the position of the heliostat around the solar field and on the tracking movement. Moreover, it also influences the shading and blocking impact of the particles: the two effects are considered together to evaluate the area of the heliostat A_{soil} whose reflection is hindered by the soiling. A soiling factor representative of soiling-related optical losses is then determined as:

$$f_{soil} = \left(1 - \frac{A_{soil}}{A_{hel}}\right) \quad (3)$$

where A_{hel} is the total surface area of each heliostat. The hourly soiling factor is computed for each sectorial division of the solar field.

The computed optical and optical 'as-clean' efficiencies are then weighted by the DNI to obtain daily values as:

$$DNI_{day} = \sum_1^{24} DNI_h \quad (4)$$

$$\eta_{opt,clean}^{day} = \frac{\sum_1^{24} \eta_{opt,clean_h} \cdot DNI_h}{\sum_1^{24} DNI_h} \quad (5)$$

$$\eta_{opt}^{day} = \frac{\sum_1^{24} \eta_{opt_h} \cdot DNI_h}{\sum_1^{24} DNI_h} \quad (6)$$

The daily soiling factor f_{soil}^{day}, which represents the impact of soiling, is then calculated as the ratio between the optical efficiency and the optical 'as clean' efficiency on a daily basis:

$$f_{soil}^{day} = \frac{\eta_{opt}^{day}}{\eta_{opt,clean}^{day}} \quad (7)$$

The rigorous prediction of the optical efficiency losses due to soiling for each sector represents an extremely valuable input for the optimization of the solar field cleaning strategy, according to the methodology described in the next section.

3 Optimization methodology

An efficient cleaning strategy definition must ultimately aim at maximizing the plant revenues (and thus the profit), defining the number of trucks to be purchased/hired to perform cleaning activities and the cleaning schedule for each solar field sector based on the trade-off between plant productivity increases and cleaning O&M costs. The resulting optimization problem can be stated as follows. Given:

- yearly profiles of incremental heliostat soiling factor for each solar field sector (provided by the model detailed in Section 2);
- yearly profiles of solar irradiance and heliostat optical 'as-clean' efficiencies;
- receiver thermal losses and power block conversion efficiencies;
- variable and fixed costs related to hiring and dispatching each cleaning crew;
- electricity selling prices;

determine:

- the required number of cleaning crews;
- the cleaning schedule of each solar field sector (i.e. the days throughout the year in which the sector is cleaned).

The optimal cleaning schedule must account for limitations on cleaning crew working hours per shift. For the sake of simplicity (but without loss of generality), the sectorial size is determined so that one crew composed of 4 operators who operate a single truck can clean one sector in one day (12 working hours) and that all the aforementioned profiles are sampled with a time-step equal to one day. The optimization aims at maximizing the yearly plant revenue, or equivalently at minimizing the sum of yearly cleaning O&M cost and costs related to lost energy production with respect to the ideal perfectly clean solar field.

In all the computations performed in this study, it is assumed that (i) a cleaning event restores the reflectance of the heliostats to their nominal value, so that $f_{soil} = 1$, hence $\eta_{opt} = \eta_{opt,clean}$ and (ii) the soiling evolution is not modified by the cleaning operations (i.e. each daily variation of soiling factor Δf_{soil} is not dependent on the current value of f_{soil}). Thus, combining 1) the assessment of the soiling factor and optical efficiency performed in Section 2, 2) the definition of a cleaning schedule for each of the N_s sectors, and 3) the assumption that the SF solar multiple and the storage are large enough to avoid defocusing and guarantee a continuous operation, the thermal energy available at the receiver can be calculated as:

$$Q_{rec}^{day} = DNI_{day} \cdot \sum_{j=1}^{N_s} A_j \cdot \eta_{opt,clean,j}^{day} \cdot f_{soil,j}^{day} \quad (8)$$

Once the thermal energy available at the receiver has been determined, it is possible to evaluate the expected electricity generation considering the thermal receiver efficiency (η_{th}) and the power block efficiency (η_{pb}). The daily thermal

receiver efficiency is computed considering constant heat losses equal to 15% of the design thermal power available at the receiver during receiver operating hours, while the power block efficiency for simplicity is assumed constant. Thermal losses and power block efficiency values are retrieved from previous publications (Binotti et al., 2017; Manzolini et al., 2019; Polimeni et al., 2018). The generated electricity is finally multiplied by the electricity price P_{el} to evaluate the total plant revenues. Costs related to the operation of the plant and routine maintenance $C_{o\&m}$ in the typical economic approach (NREL, 2014) are expressed in terms of $/MWh; therefore, they can directly be subtracted from the electricity price for an accurate assessment of the actual revenues. The cleaning costs (C_{cl}) are considered separately and expressed more in detail: they comprise the purchase/rent of the cleaning truck(s) and the hiring of the specialized operators that perform the cleaning activities. The yearly total profit (TP) is eventually calculated as:

$$TP = \sum_{i=1}^{365} \sum_{j=1}^{N_s} \eta_{opt,clean_{ji}}^{day} \cdot f_{soil_{ji}}^{day} \cdot A_j \cdot DNI_{day,i} \cdot \eta_{th,i} \cdot \eta_{pb} \cdot (P_{el} - C_{o\&m}) - C_{cl} \quad (9)$$

Where the index i denotes the current day of the year and the index j denotes the sectors of the solar field. Thus, $\eta_{opt,clean_{day,ji}}$ indicates the average daily optical efficiency of the j-th sector on the i-th day for a perfectly clean solar field, and $f_{soil_{day,ji}}$ is the correspondent daily soiling factor (that depends on the cleaning schedule).

Two scenarios are then considered with regards to the cost of cleaning operations:

- "owned trucks", which considers the trucks to be purchased by the plant operator and the truck operators to be hired for the whole year;
- "on-call", which considers the trucks to be rented by the plant operator every time a cleaning is needed, together with the service of the required truck operators.

In the "owned trucks" scenario, the yearly cleaning costs are expressed as:

$$C_{cl} = C_{cl,var} \cdot n_{cl} + C_{cl,fix} \cdot n_{tr} \quad (10)$$

where $C_{cl,var}$ represents the variable cleaning costs, n_{cl} the number of cleanings per year, $C_{cl,fix}$ the fixed cleaning costs, and n_{tr} the number of purchased trucks. The variable cleaning costs account for the water and fuel usage, while the fixed cleaning costs account for the trucks purchase and maintenance and the salary of the truck operators.

In the "on-call" scenario, the yearly cleaning costs are expressed as

$$C_{cl} = C_{cl,rent} \cdot n_{cl} + C_{call} \cdot n_{call} \quad (11)$$

where $C_{cl,rent}$ represents the rent cleaning costs, n_{cl} the number of cleanings per year, C_{call} the cost of each cleaning truck call, and n_{call} the number of truck calls. The rent cleaning costs account for the rental of the trucks, and the payment of the cleaning shifts performed by the truck operators, while the "call" cost sets a fee that has to be paid every time a cleaning truck is rented.

Since cleaning costs represent only a limited fraction of total operating costs, the adoption of the overall yearly revenues as described in Eq. (9) as the problem objective function complicates the convergence to the optimal cleaning schedule since the sensitivity of the objective function with respect to the optimization variables is limited. It is therefore useful to define an auxiliary objective function that is more representative of the trade-off between cleaning costs and improved thermodynamic performance, while still accounting for the effect on yearly power plant revenues. This alternative figure

of merit is the *total cleaning cost* (TCC), defined as the sum of the actual operating cleaning cost C_{cl} described above in details and the so-called degradation cost C_{deg}, which accounts for the electricity generation losses due to soiling and is computed as:

$$C_{deg} = \sum_{i=1}^{365} \sum_{j=1}^{N_s} \eta_{opt,clean,ji}^{day} \cdot \left(1 - f_{soil,ji}^{day}\right) \cdot A_j \cdot DNI_{day,i} \cdot \eta_{th,i} \cdot \eta_{pb} \cdot (P_{el} - C_{o\&m}) \quad (12)$$

Consequently, the total cleaning cost, which serves as the optimization objective function, is computed as:

$$TCC = C_{cl} + C_{deg} \quad (13)$$

Examining Eqs. (9), (12), and (13) it is easy to see that the minimum of TCC corresponds to the maximum of TP.

3.1 Heuristic approach

The heuristic approach to cleaning scheduling does not rely on the formal mathematical optimization of the described problem, but consists in the definition of a rule-based strategy which is then tuned by acting on its characteristic operating parameters: number of cleaning trucks n_{tr} involved in cleaning operations, and sectorial cleaning interval d^{cl}, representing the number of days after which a solar field sector is cleaned again. Every d^{cl} days, all n_{tr} cleaning trucks are deployed, cleaning the maximum number of sectors every day in a pre-defined order until all solar field sectors have been cleaned.

For a given number of trucks n_{tr}, there will be a minimum cleaning interval d_{min}^{cl} which corresponds to continuously performing cleaning operations at the maximum rate allowed by the number of deployed trucks. However, cleaning intervals longer than d_{min}^{cl} might be preferable, since the increase in plant production comes at the expense of the direct costs associated with the cleaning operations. The heuristic algorithm parameters d^{cl} and n_{tr} are therefore tuned in each case study by means of a parametric performance assessment: for every admissible combination of n_{tr} and $d^{cl} \in [d_{min}^{cl}, 365]$, the yearly plant performance is evaluated. The optimal combination of cleaning trucks n_{tr} (to be purchased or rented according to the operating scenario) and sectorial cleaning interval d^{cl} is then simply the combination that achieves the lowest total cleaning cost. Figure 1a shows the results of the parametric analysis: for each considered number of trucks n_{tr} the TCC described in Eq. (13) is computed and reported as a function of the annual number of cleanings, which depends on the cleaning interval d_{cl}. The optimal number of cleanings for a given number of trucks is labelled with a blue asterisk while the best combination of cleaning interval and number of trucks is labelled with a red bigger asterisk. The maximum allowable number of trucks and cleanings per year is limited to 8 and 60, respectively, for the sake of better comprehensibility of the picture. In Figure 1b the TP described in Eq. (9) is displayed as a function of the annual number of cleanings, which depends on the cleaning interval d_{cl}. The blue and large red asterisks denote, respectively, the best number of cleanings for each given number of trucks and the overall optimal. The comparison between Figure 1a and Figure 1b indicates that the same optimal combination of cleaning interval and number of trucks corresponds to both the maximum total profit (TP) and the minimum total cleaning cost (TCC), as expected.

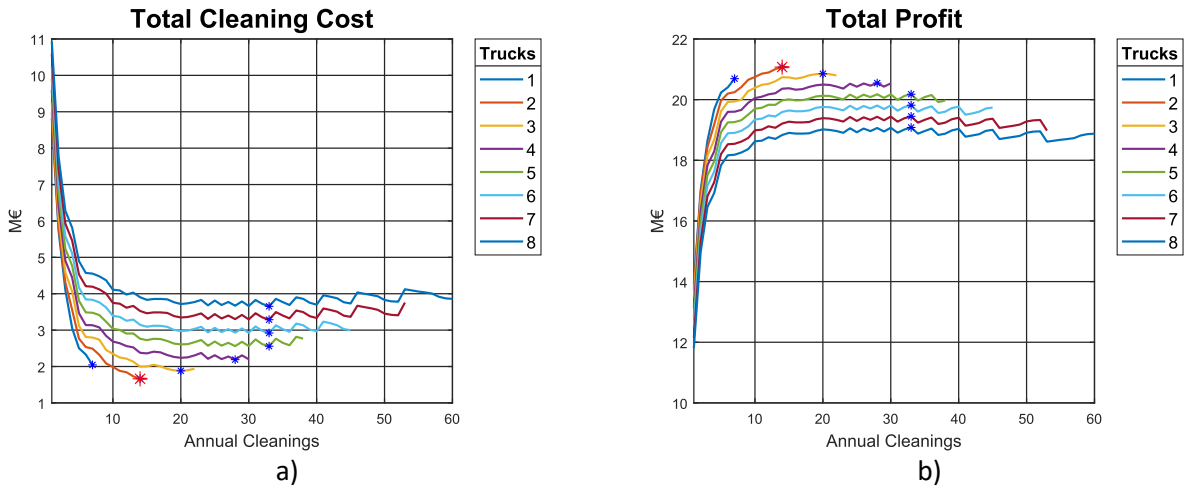


Figure 1. Parametric heuristic algorithm

The performance of the tuned heuristic approach serves as the benchmark to quantify the advantages deriving from the proposed advanced approach to cleaning scheduling optimization, via the Mixed Integer Linear Programming (MILP) model presented in the next section.

3.2 MILP model

Mixed Integer Linear Programming (MILP) denotes a class of optimization problems featuring both integer and continuous variables and characterized by a linear objective function and linear problem constraints. Many scheduling optimization problems arising in production planning and logistics are formulated as MILPs because of the following two substantial advantages:

- Very efficient solvers are available commercially and they are able to tackle large scale real-world problems;
- The convexity of the relaxed problem (a linear program where the integrality condition is relaxed) allows identifying a rigorous assessment of the global optimality of a solution (optimality gap).

A MILP formulation of the optimal cleaning scheduling problem was therefore developed, to formally identify the global optimal scheduling solution that minimize the total cleaning cost (Eq. (13)). It is important to note that the optimization accounts for the trade-off between increasing cleaning costs due to a higher cleaning frequency and increased plant productivity. Thus, the global optimum identified by the MILP approach might be associated to higher direct cleaning costs with respect to the heuristic approach, while obtaining higher yearly revenues by virtue of the enhanced plant productivity. The independent decision variables of the optimization problem are:

- the cleaning schedule for each solar field sector, indicating the days of the year in which each sector is to be cleaned;
- the number of trucks involved in the cleaning activities (to be purchased/rented).

The constraints defining the mathematical formulation of the cleaning scheduling optimization problem are presented hereafter.

Let $\mathcal{S} = \{1,2,\dots,N_s\}$ be the set of sectors of the solar field and $\mathcal{T} = \{1,2,\dots,365\}$ be the set of days in the year. For each sector $s \in \mathcal{S}$, the binary cleaning scheduling variable $z_{s,\ell,t}$ is equal to 1 if, in day $t \in \mathcal{T}$, mirrors were last cleaned in day $\ell \in \mathcal{T}$. Variable $z_{s,\ell,t}$ is cyclic in time with respect to temporal index t, representing a periodic cleaning schedule across consecutive years (i.e., the heliostats' soiling status on the 31st of December represents the day-ahead condition for the 1st

of January). The diagonal elements of each bidimensional matrix $z_{s,\ell,t}$ with respect to temporal indexes t and ℓ (henceforth referred to as $Z^s \subseteq \mathbb{R}^{365\times365}$), or equivalently all variables $z_{s,\ell,t}$ with $t = \ell$, assume the value 1 if the sector was last cleaned that same day. They therefore represent the cleaning schedule of sector s. In each day $t \in \mathcal{T}$ and for each sector $s \in \mathcal{S}$, it is possible to univocally identify a single day in which the sector was last cleaned as:

$$\sum_{\ell\in\mathcal{T}} z_{s,\ell,t} = 1 \qquad \forall\, s \in \mathcal{S}, t \in \mathcal{T} \qquad (14)$$

On the other hand, if the mirrors were not cleaned on a given day $\hat{\ell} \in \mathcal{T}$ (i.e. $z_{s,\hat{\ell},\hat{\ell}} = 0$), all variables $z_{s,\hat{\ell},t}$ must be equal to zero since sector s was never cleaned during day $\hat{\ell}$:

$$z_{s,\ell,\ell} \cdot 365 \geq \sum_{t\in\mathcal{T}} z_{s,\ell,t} \qquad \forall\, s \in \mathcal{S}, \ell \in \mathcal{T} \qquad (15)$$

With each cleaning scheduling variable $z_{s,\ell,t}$ is associated the parameter $\tilde{f}_{s,\ell,t}$, which indicates the soiling factor for the mirrors of sector s in day t, in case they were last cleaned in day ℓ. All potential soiling factors $\tilde{f}_{s,\ell,t}$ are computed according to the soiling model described in (Picotti et al., 2018). The actual sector soiling factor $f^{day}_{soil_{ji}}$ associated to the scheduling plan $z_{s,\ell,t}$ can be therefore calculated, in each day $t \in \mathcal{T}$, as:

$$f^{day}_{soil_{ji}} = \sum_{\ell\in\mathcal{T}} z_{s,\ell,t}\, \tilde{f}_{s,\ell,t} \qquad \forall\, s \in \mathcal{S}, t \in \mathcal{T} \qquad (16)$$

Constraint (14) already implies that one and only one of all potential soiling factor values $\tilde{f}_{s,\ell,t}$ must be considered in each day t, or in other words that for each column t only one of the rows l can have a non-zero value of $z_{s,\ell,t}$. Optimality of the solution will imply that, within the pool of "active" rows (non-zero diagonal variable $z_{s,\ell,\ell}$, constraint (15)) will be selected the one associated to the lowest soiling factor $\tilde{f}_{s,\ell,t}$. If the optimal solution features a cleaning operation of the sector on day ℓ, the active variable will be the diagonal variable $z_{s,\ell,\ell}$, otherwise it will be the variable $z_{s,\ell,t}$ with the lowest non-negative difference $\ell - t$ (accounting for the cyclicity of temporal indexes). To speed up convergence (by tightening the problem formulation) it is useful to introduce an additional constraint which tends to "group" the non-zero entries in the matrix Z^s, and guide the solution algorithm towards the optimal variables configuration:

$$z_{s,\ell,t} \leq z_{s,\ell,t-1} \qquad \forall\, s \in \mathcal{S}, t, \ell \in \mathcal{T}, t \neq \ell \qquad (17)$$

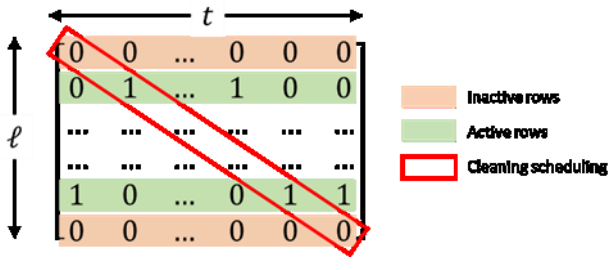


Figure 2. Cleaning scheduling matrix Z^s for sector $s \in \mathcal{S}$

A visual interpretation of matrix Z^s is provided in Figure 2: for a given sector, each column t of Z^s is associated to a day of the year, while each row ℓ represents the last day of the year, from the temporal perspective of t, in which s was cleaned. The diagonal of Z^s is the cleaning schedule of sector s, and each of its elements $z_{s,\ell,\ell}$ activates the corresponding binary variables on the ℓ^{th} row.

The sum of diagonal elements of all matrixes Z^s yields a vector whose elements indicate the number of cleaning operations taking place in a given day, which correspond to the number of trucks (according to the assumption that the sectors are sized such that one crew operating one truck cleans one sector per day). In the "owned trucks" scenario, the maximum number of simultaneous cleaning operations determines the requirement in terms of purchased cleaning trucks:

$$\sum_{s \in \mathcal{S}} z_{s,t,t} \leq n_{tr} \qquad \forall\, t \in \mathcal{T} \qquad (18)$$

As for the "on call" scenario, a fixed cost must be paid each time new trucks are called to take part in the cleaning operations (Eq. (11)). To account for the fixed call cost in the MILP formulation objective function, it is necessary to introduce the non-negative integer variable c_t, equal to the number of new trucks which were not present the day before that are performing cleaning duties during day $t \in \mathcal{T}$:

$$c_t \geq \sum_{s \in \mathcal{S}} z_{s,t,t} - \sum_{s \in \mathcal{S}} z_{s,t-1,t-1} \qquad \forall\, t \in \mathcal{T} \qquad (19)$$

The number of yearly truck calls is thus equal to the summation of c_t:

$$n_{call} = \sum_{t \in \mathcal{T}} c_t \qquad (20)$$

The optimization problem is formulated in MATLAB, using the extension YALMIP (Lofberg, 2004), and it is solved using the commercially available solver GUROBI (Guorobi Optimization, 2018).

4 Case studies

The heuristic and deterministic optimization methodologies were applied to two ST plants located in Woomera in South Australia (31°12′S 136°48′E) and in Abu Dhabi in the United Arab Emirates (24°24′N 54°42′E). The two areas were selected as they have different characteristics in terms of latitude, climate, and airborne dust concentration.

Two different solar fields were generated using SolarPilot (NREL, 2017) assuming 700 MW as target power on the receiver on the summer solstice. Receiver geometry, tower height and heliostats size were set according to literature data for the Crescent Dunes plant (Mehos et al., 2017; SolarReserve), while heliostat total reflected image error was assumed equal to the SolarPilot default value of 3.07 mrad. The two simulated solar fields, the related sectors, and the representative heliostat for each sector (red dots) are represented in Figure 3. The characteristics of the two heliostats fields are reported in Table 1, together with their performance on the summer solstice.

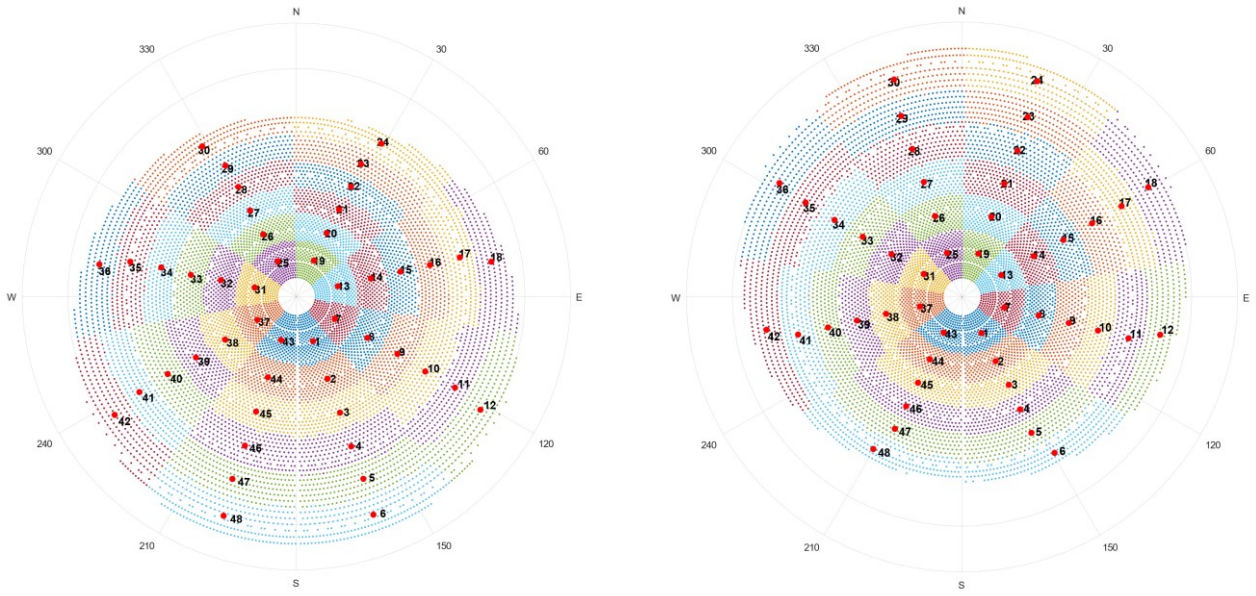


Figure 3. Solar field a) Woomera ; b) Abu Dhabi

Table 1 – Solar field design assumptions and performances

Design Assumptions		
Direct Normal Irradiation [W/m²]	**900**	
Location	**Abu Dhabi**	**Woomera**
Geographical Coordinates	24°24'N 54°42'E	31°12'S 136°48'E
HTF type	Solar Salts	Solar Salts
Receiver size		
Height [m]	30.5	30.5
Diameter [m]	15.8	15.8
Tower height [m]	195	195
Field type	Surrounded	Surrounded
Minimum radius of the field [m]	126.7	126.7
Maximum radius of the field [m]	1626	1626
Number of heliostats	10328	10336
Heliostat size [m²]	11.3 x 10.4	11.3 x 10.4
Heliostat reflectivity	0.95	0.95
Heliostat total reflected image error [mrad]	3.07	3.07
Performance		
Sun Position		
Zenith	0.95	7.75
Azimuth	180	0
Optical efficiency	**0.652**	**0.651**
Power on the receiver [MW]	**701.6**	**701.2**
Receiver thermal losses [MW]	**105**	**105**
Power block efficiency	**0.35**	**0.35**

The number of sectors considered for the two case studies is 48, with 6 radial and 8 angular partitions in order to have similar values of optical efficiency within the sectors. This provided sectors made of the same number of heliostats (±1) such that each could be cleaned in one day (12 working hours) using one truck. The average cleaning speed of 2000 m^2/h has been assumed as a reasonable value within the cleaning speed range reported in Pfahl et al. (2017). Moreover, it is a good compromise between computational efforts and accuracy of the model. A higher number of sectors would greatly increase the computational time of the optimization, while a smaller number of them would hinder the effectiveness of the optimization as the sectors would include heliostats whose soiling factor and optical efficiency could differ

significantly. A parametric analysis on the influence that different cleaning speeds and sectorizations of the solar field have on the outcomes of the optimization is discussed in Section 5.1.2.

For each sector, the nominal optical efficiency $\eta_{opt,clean}$ assigned to the sector representative heliostat located in its geometrical barycentre is computed as the average "as-clean" optical efficiency of all the heliostats composing it.

The cleaning strategy optimizations were performed for the two selected sites on hourly time step to calculate the optical efficiency and actual thermal energy on the receiver. The time step coincides with the availability of the environmental conditions measured by the local weather stations. The one located in Woomera provides data regarding DNI, wind speed, and air temperature. Since data about dust concentration are not locally available for the Australian site, PM10 (particulate matter whose aerodynamic diameter is smaller than 10μm) measurements are obtained from the location of Moolawatana, in SA, as the climate and the environmental characteristics are similar to Woomera. The PM10 data are adapted to fit in the assumed dust size distribution, chosen as 'rural' from Seinfeld and Pandis (1998), to be as close as possible to the simulated environment. Weather data for Abu Dhabi are obtained from the SolarPILOT database while the average monthly dust concentration measured in Mushrif Park (UAE) is used to scale the hourly dust concentration measured in Moolawatana.

The main economic parameters are reported in Table 2 for both "owned trucks" and "on call" cost structures. Finally, given the size of the heliostats, the number of heliostats per sector, and the cleaning speed, it is assumed that a cleaning operation requires two six-hours-shifts of a team made by two operators who operate a truck. Each cleaning crew composed by 4 operators and a truck is then able to clean one sector per day.

Table 2. Economic assumptions

	"owned trucks"	**"on call"**
Truck operator salary [$/yr]	80000	-
Truck operator hiring [$/day]	-	250
Truck rent cost [$/day]	-	250
Truck purchase cost [$]	150000	-
Truck maintenance cost [$/yr]	15000	-
Water and fuel cost [$/m^2]	0.01	-
Call cost [$/call]	-	1000
Depreciation time [yr]	4	-
Electricity price [$/MWh]	50	50

To further demonstrate the capabilities of the model and assess the scheduling impact of different locations, different values of airborne dust concentration were used, as well as different economic assumptions regarding the selling price of electricity: the measured PM10 values have been halved, increased five and ten times, while the electricity price has been increased and decreased by 50%. The whole set of performed scenarios (including the two base cases) is summarized in Table 3.

Table 3. Cleaning optimization scenarios

Location	**Electricity Price [$/MWh]**	**Average PM10 [μg/m^3]**
Woomera	50	4.441
Abu Dhabi	50	126.315
Woomera x 0.5	50	2.220
Woomera x 5	50	22.203
Woomera x 10	50	44.406

Woomera LP	25	4.441
Woomera HP	75	4.441

5 Results

For the base case of Woomera, the reduction of Total Cleaning Cost (TCC) for the MILP compared to the heuristic approach is 3.75% (62.4k$) for the "owned trucks" scenario and 15.39% (245.1 k$) for the "on call" scenario. Figure 4 illustrates the outcomes of the MILP cleaning optimization for the "owned trucks" case for Woomera. Figure 4a shows the average yearly optical efficiency ($\eta_{opt,clean}$) of each sector of the field, computed as the average "as-clean" optical efficiency of all the heliostats composing each sector, while Figure 4b represents the corresponding average yearly soiling factor without cleanings ($f_{soil,noclean}$), computed for each sector-representative heliostat and then applied to all the heliostats belonging to the same sector. Figure 4c finally depicts the results of the MILP optimization. The number of annual cleanings for each sector is displayed in the sector's geometrical barycentre. The resulting average yearly soiling factor ($f_{soil,clean}$) is also illustrated through the colour map.

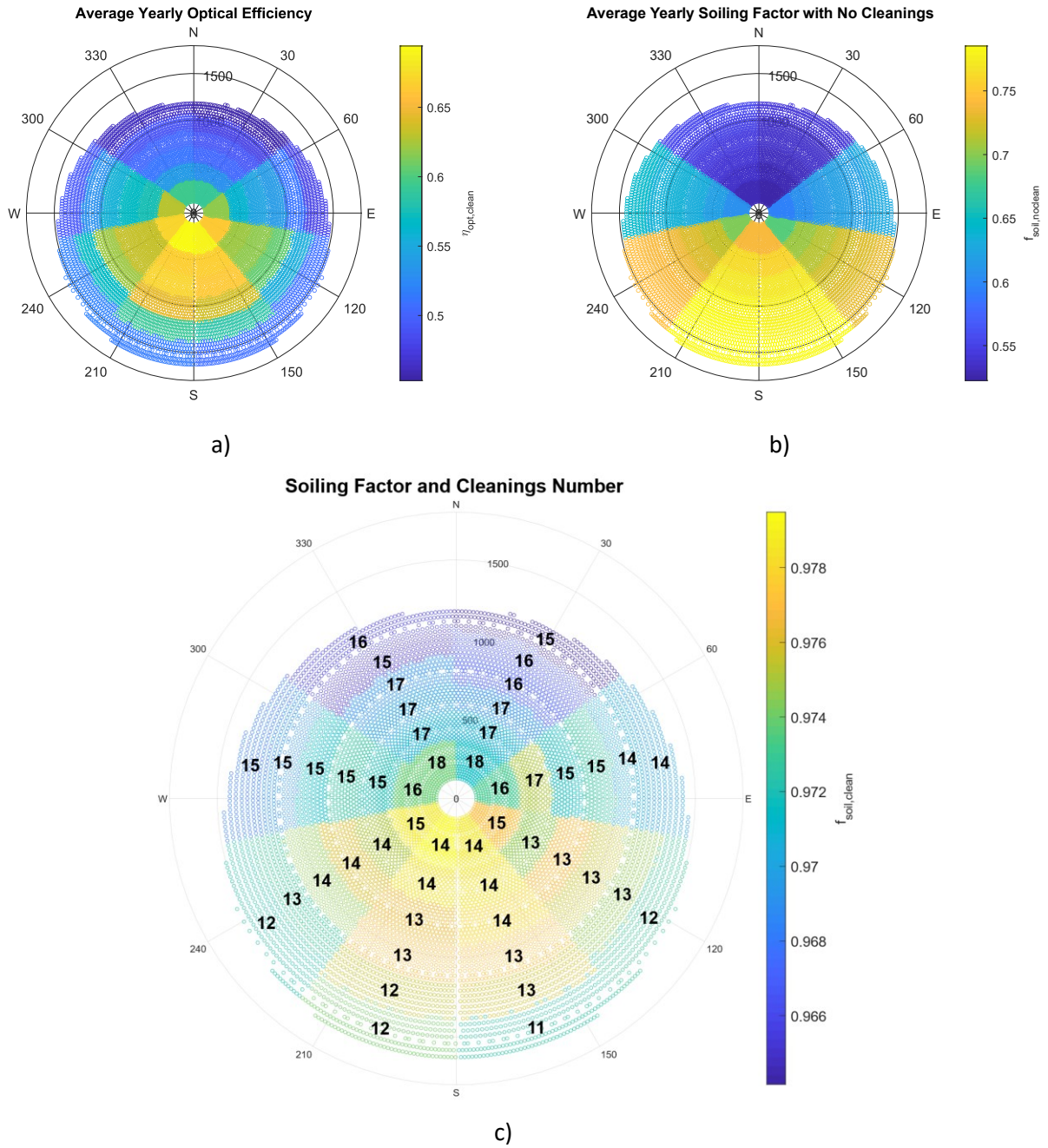
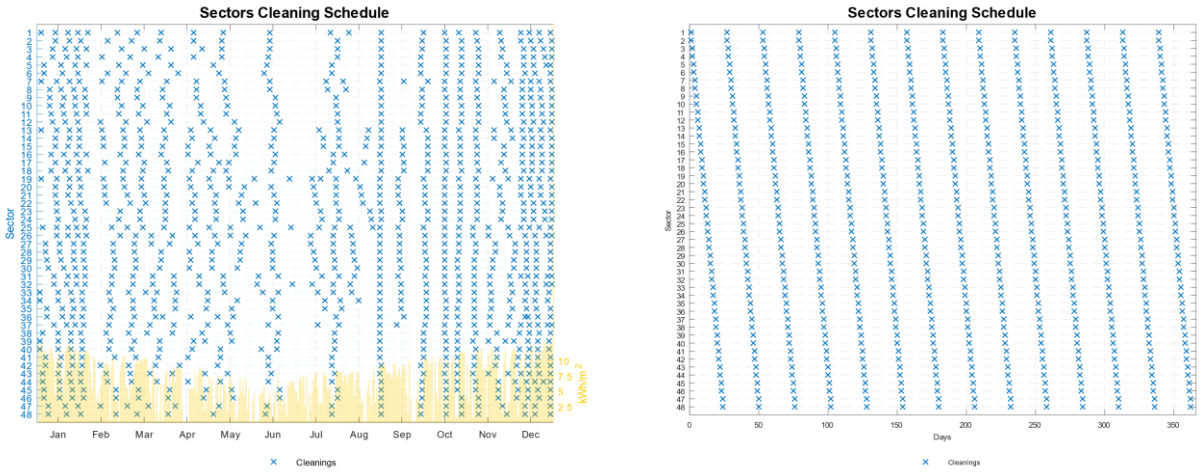


Figure 4. Cleaning summary and impact - Woomera - "owned trucks" ; a) Average yearly optical efficiency ; b) Average yearly soiling factor without cleanings ; c) Optimization outcomes

It is worth noting that the sectors that are cleaned more frequently have either high yearly average optical efficiency (especially those sectors that are close to the tower) or low average yearly soiling factors without cleanings $f_{soil,noclean}$ (i.e. they are subjected to more soiling). The resulting lower yearly average soiling factor ($f_{soil,clean}$ in Figure 4c) occurs in the sectors with the lower yearly average optical "as-clean" efficiency, despite the high cleaning frequency, as it may be noticed looking at the darker tonalities in the upper part of the graph in Figure 4c. This is in agreement with their smaller contribution in terms of thermal power reflected onto the receiver. It is also possible to recognize that the sectors with the lower $f_{soil,noclean}$ are the ones located further in the northern part of the solar field (in a ST plant located in the Southern Hemisphere). This can be explained by the lower average tilt angles of these heliostats, leading to higher soiling rates, in accordance to the model developed in Picotti et al (2018). Besides the annual number of cleanings and trucks required, the precise cleaning scheduling and timing is the most peculiar aspect of the MILP optimization: Figure 5a

shows the cleaning events for each sector along the whole year (sector numbers refer to Figure 3). It can be seen the higher cleaning frequency of either the sectors closer to the tower or the northerner sectors is in accordance to Figure 4c. It is also interesting to note that the cleaning frequency is higher during summer (December to February in Australia), when the available DNI, the overall "as-clean" optical efficiency, and the receiver thermal efficiency are higher, and lower during winter (June to August in Australia), when the available DNI, the overall "as-clean" optical efficiency, and the receiver thermal efficiency are lower.



a) b)

Figure 5. Cleaning schedule – Woomera – "owned trucks": a) MILP ; b) Heuristic

The corresponding cleaning schedule for the heuristic approach is displayed in Figure 5b. It is clearly observable the cleaning pattern is much more regular, which regardless of the different soiling factor and optical efficiency of the various sectors suggests cleaning each sector 14 times per year. Although both approaches assess that the optimal number of cleaning trucks is two, the number of annual cleanings is higher for the MILP optimization (699 vs 672). This results in higher direct cleaning costs, but the enhanced optical efficiency leads to a higher power generation, lower TCC, and higher profit. The superiority of the MILP approach resides in the smarter allocation of the cleanings, increasing their frequency during high-productivity periods for those sectors that are more soiled or with higher "as-clean" optical efficiency and decreasing their frequency when they are less needed. Overall, for the analysed case, the MILP approach reduces the TCC by 3.75%.

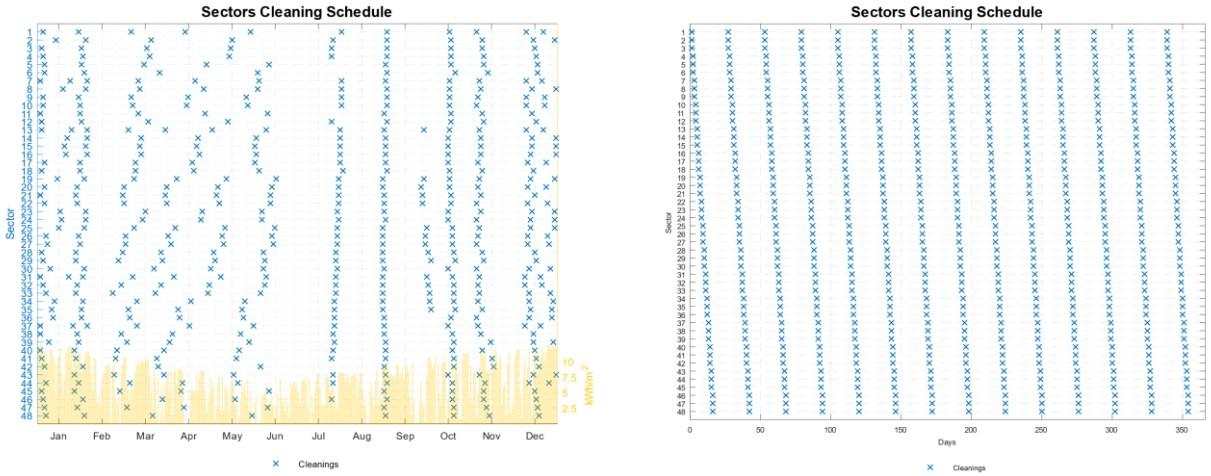
When considering the "on call" policy for the same case, the economic advantage of the MILP solution over the heuristic increases, owing to the higher degrees of freedom of this policy. Although the number of calls is increased from 42 to 58, the number of cleanings is reduced from 672 to 526, and savings on both the degradation cost and the direct cleaning operations is obtained by allocating the cleanings in the most suitable times. Figure 6a and Figure 6b allow a visual comparison between the MILP and heuristic optimal cleaning schedules, outlining the more scattered optimal strategy of the MILP approach which yields a significant 15.39% decrease of the TCC.

Table 4 reports the monthly values of DNI and average airborne dust concentration, together with the related number of cleanings, to highlight their efficient scheduling obtained with the MILP optimization for both the "owned trucks" and "on call" scenarios. As the latter has a higher flexibility regarding the deployment of cleaning trucks, the difference between winter and summer months is much higher.

A summary of the comparison between the MILP and the heuristic cleaning optimization for the two scenarios is reported in Table 5.

Table 4. Monthly cleanings summary – Woomera

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
"owned trucks"	60	56	62	60	55	51	49	62	60	62	60	62
"on call"	79	28	49	31	31	30	30	23	43	56	48	78
DNI [kWh/m^2]	328	211	220	171	143	107	166	189	191	240	235	304
Dust Concentration [µg/m^3]	4.0	2.4	3.0	4.7	3.4	1.8	4.2	5.5	2.8	5.4	3.7	11.8



a) b)

Figure 6. Cleaning schedule – Woomera – "on call": a) MILP ; b) Heuristic

Table 5. MILP vs Heuristic comparison summary – Woomera

	"owned trucks"		"on call"	
	MILP	Heuristic	MILP	Heuristic
Trucks/Calls	2	2	58	42
Cleanings	699	672	526	672
C_{cl} [k$/yr]	919.2	912.5	715.1	881.5
C_{deg} [k$/yr]	680.9	750.1	633.0	711.7
TCC [M$/yr]	1.60	1.66	1.35	1.59
TP [M$/yr]	21.14	21.07	21.39	21.14

The cleaning optimization was also applied to the case study of Abu Dhabi. The TCC improvement (reduction) of the MILP versus the heuristic approach for the "owned trucks" and "on call" policies is 0.68% (26.3 k$) and 12.15% (477.5 k$), respectively. Figure 7 illustrates the outcomes of the MILP cleaning optimization for the "on call" case. Similar to the Woomera case, the most frequently cleaned sectors are those whose yearly average optical efficiency is higher (Figure 7a) or whose soiling factor with no cleanings ($f_{soil,noclean}$) is lower (Figure 7b). However, since Abu Dhabi is in the Northern Hemisphere, the location of the heliostats with lower average tilt angles (i.e. the most soiled ones) are in the southern part of the solar field. Due to the much higher average airborne dust concentration in the UAE compared to South Australia, the number of cleanings per sector is considerably higher (see also the significantly lower average yearly soiling factor with no cleanings $f_{soil,noclean}$).

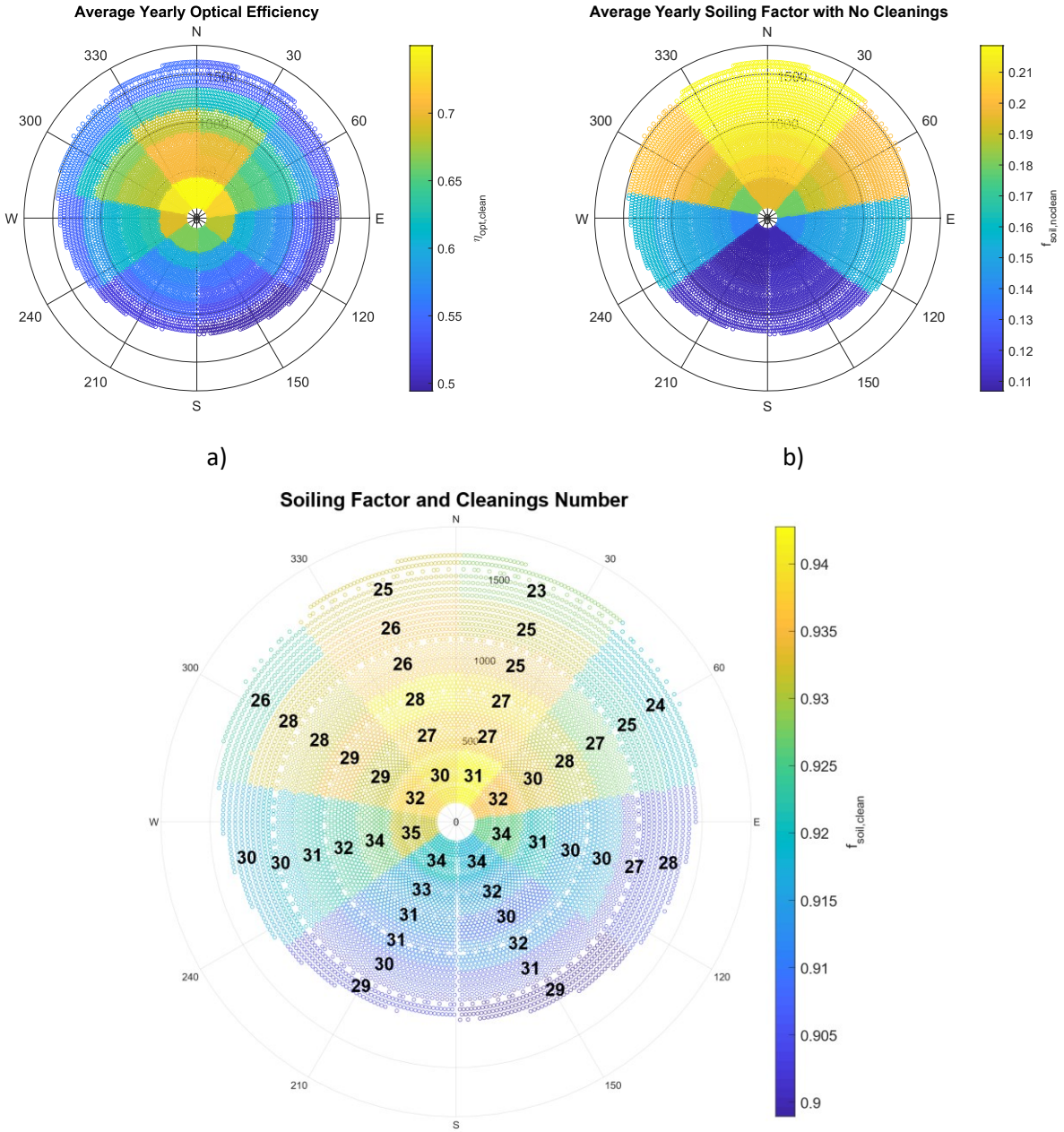


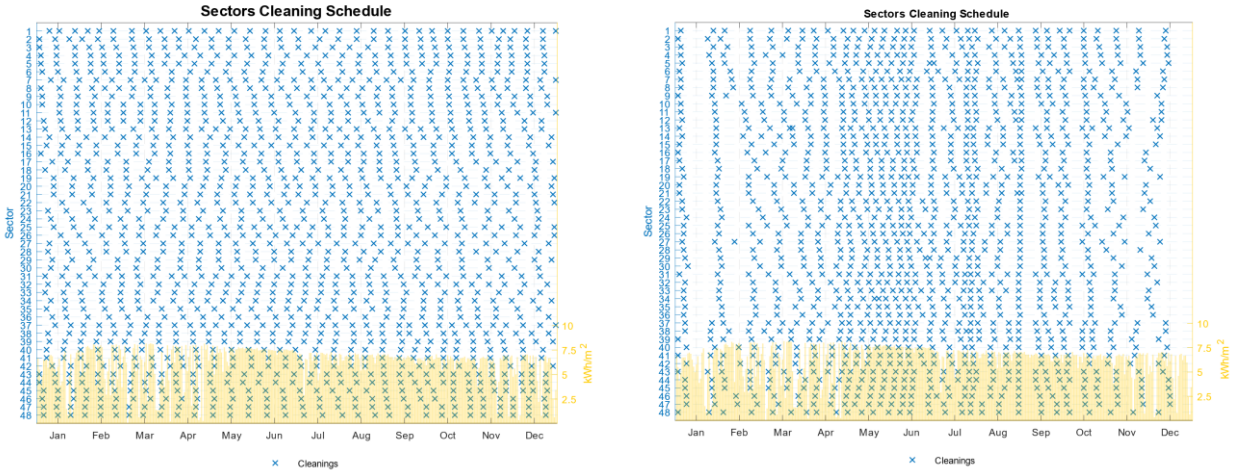
Figure 7. Cleaning summary and impact – Abu Dhabi – "on call": a) Average yearly optical efficiency ; b) Average yearly soiling factor without cleanings ; c) Optimization outcomes

As for the optimization performed for the location of Woomera, summer months (June to August in the UAE) experience the higher cleaning frequency, especially for the "on call" scenario, as reported in Table 6. The increased cleaning frequency is due to the higher airborne dust concentration measured in Abu Dhabi.

The graphical representation of the detailed cleaning schedules depicted in Figure 8 also confirms the described trend, emphasizing the more frequent cleaning of the southernmost heliostats and during summer (more clearly visible in Figure 8b).

Table 6. Monthly cleanings summary – Abu Dhabi

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
"owned trucks"	148	138	155	150	155	150	155	155	150	155	147	118
"on call"	88	75	102	127	186	177	168	129	121	114	78	41
DNI [kWh/m^2]	171	188	160	173	230	225	201	208	206	208	181	162
Dust concentration [µg/m^3]	111	101	103	150	135	145	178	154	140	116	91	90



a) b)

Figure 8. Cleaning schedule – Abu Dhabi: a) "owned trucks" ; b) "on call"

Compared to the heuristic approach, the MILP optimization of the "owned trucks" cleaning strategy improves the TCC by smartly allocating the significantly increased number of cleanings and decreasing the number of trucks. In the "on call" case, the MILP optimization both creates better 'clusters' of continuous cleanings to diminish the number of truck calls (n_{call} in Eq. (11)), and also intensify the cleanings when and where they are more needed, thus reducing both the operational and degradation related cleaning costs, and hence the TCC. Table 7 summarizes the main parameters of the cleaning optimizations performed for the case of Abu Dhabi.

Table 7. MILP vs Heuristic comparison summary – Abu Dhabi

	"owned trucks"		"on call"	
	MILP	Heuristic	MILP	Heuristic
Trucks/Calls	4	5	92	145
Cleanings	1446	1824	1406	1392
C_{cl} [k$/yr]	1850.0.	2316.7	1848.1	1883.6
C_{deg} [k$/yr]	1970.7	1530.4	1603.7	2045.7
TCC [M$/yr]	3.82	3.85	3.45	3.93
TP [M$/yr]	17.90	17.87	18.27	17.79

5.1 Sensitivity analysis

The optimization scheme for the two scenarios described in the previous section has been applied to the base case of Woomera for different dust concentrations and electricity prices (see Table 3), and solar field sectorizations (see Table 10). The outcomes of such sensitivity analyses are described and analysed in the following sub-sections.

5.1.1 Dust concentration and price variations

The airborne dust concentration is a parameter of paramount importance when evaluating the soiling-related optical efficiency losses of the heliostats since it strongly affects the amount of dust that is deposited on the reflective surfaces.

The values measured in Moolawatana and adopted for the base case of Woomera have been halved, increased 5 and 10 times, to properly assess the relevance they have on the outcomes of the optimization.

For both "owned trucks" and "on call" scenarios, the share of the TCC on the TP increases as the dust concentration is increased, as reported in Table 8 and Table 9. This reflects the necessity for more frequent cleanings in dustier environments. Since the TCC is more relevant for the scenarios that consider higher concentration of dust in air, its improvement has a more relevant impact on the total profit of the plant: as reported in Table 8, considering the "owned trucks" scenario, the TCC decrease obtained with the MILP optimization is larger for the lowest-dust case (7.43%) than for the highest-dust case (4.60%). Nevertheless, the impact on the total profit is 0.43% for the former, and 1.29 % for the latter, since the impact of the TCC on the TP grows from 5.36% to 26.37%, respectively. The same trend is observed for the corresponding cases in the "on call" scenario, as summarized in Table 9.

As expected, the higher the dust concentration in air, the higher is the number of trucks purchased or called, as well as the number of cleanings per year. Concerning the "owned trucks" scenario, Table 8 shows that for the four dust concentrations analysed, the trucks number grows from just 1 to 6, as the annual cleanings rise from 364 to 2054. Coherently for the "on call" scenario, Table 9 shows that the number of calls grows for 40 to 194, as the annual cleanings rise from 379 to 1597. Figure 9a and Figure 9b depict the cleaning schedules for the lowest-dust and highest-dust cases for the "owned trucks" scenario. It is remarkable to observe that once again the cleanings are less frequent during winter (June to August in South Australia), and the northernmost sectors require an higher number of cleanings.

Moving to the sensitivity analysis on the price of electricity, the HP case has a higher number of cleanings and higher number of trucks purchased/called. This reflects the better convenience of investing more money for cleaning operations to generate more electricity and more profit. The opposite occurs when the electricity price is lower. Figure 10a and Figure 10b depict the cleaning schedules for the LP and HP cases, clearly showing the higher cleaning frequency in the second case. A comprehensive summary of the main parameters for all the sensitivity analyses described in this section is reported in Table 8 and Table 9. The results of these analyses stress the importance of developing optimized cleaning strategies as they vary from case to case. In addition, the developed optimization algorithm always significantly improves the TCC and thus the profit of the plant. Finally, Table 8 and Table 9 report the computational time required for each case. The optimizations were performed on a Windows virtual machine with 16 virtual processors (2.3 GHz of standard frequency) of an Intel® Xeon® E5-2686 v4 CPU chipset and 122 Gib of RAM.

Table 8. Sensitivity analysis summary - "owned trucks"

	Owned Trucks					
	Woomera	Woomera x0.5	Woomera x5	Woomera x10	Woomera HP	Woomera LP
Tot Profit [M$/y]	21.14	21.58	19.31	17.99	32.99	9.41
TCC [M$/y]	1.60	1.16	3.43	4.74	1.97	1.11
C_{cl} [k$/y]	919.2	463.2	1840.1	2746.8	923.7	463.2
C_{deg} [k$/y]	680.9	694.2	1590.4	1997.2	1040.9	641.9
Electricity [GWh/y]	474.3	474.0	454.7	446.0	474.4	459.1
N TRUCKS	2	1	4	6	2	1
N CLEANS	699	364	1405	2054	717	364
TP INCREASE	0.30%	0.43%	0.88%	1.29%	0.30%	0.92%
TCC DECREASE	**3.75%**	**7.43%**	**4.69%**	**4.60%**	**4.82%**	**7.18%**
TCC share on TP	7.57%	5.36%	17.77%	26.37%	5.95%	11.75%

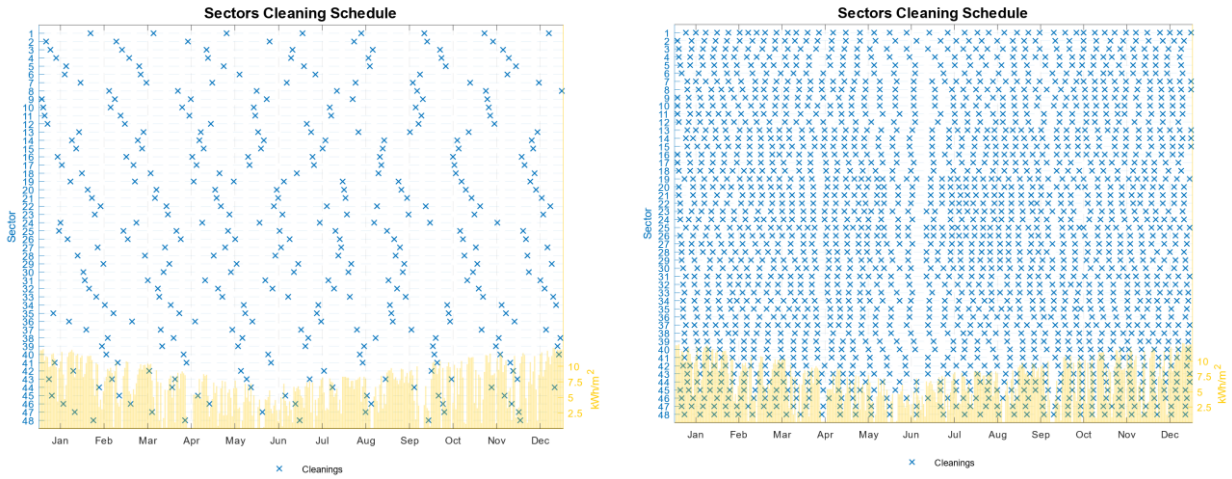
Computational time [s]	793056	3061385	18184	26322	293784	4525604

467

468 *Table 9. Sensitivity analysis summary - "on call"*

	On Call					
	Woomera	Woomera x0.5	Woomera x5	Woomera x10	Woomera HP	Woomera LP
Tot Profit [M$/y]	21.39	21.77	19.83	18.72	33.31	9.59
TCC [M$/y]	1.35	0.96	2.90	4.01	1.65	0.93
C_{cl} [k$/y]	715.1	513.4	1567.1	2188.9	882.5	492.0
C_{deg} [k$/y]	633.0	448.7	1334.1	1822.1	770.9	435.4
Electricity [GWh/y]	475.3	479.3	460.2	449.8	478.2	468.7
N CALLS	58	40	153	194	83	36
N CLEANS	526	379	1132	1597	640	365
TP INCREASE	1.16%	0.94%	3.69%	5.50%	0.98%	1.91%
TCC DECREASE	**15.39%**	**17.37%**	**19.55%**	**19.59%**	**16.32%**	**16.20%**
TCC share on TP	6.30%	4.42%	14.63%	21.42%	4.96%	9.67%
Computational time [s]	425087	619714	44906	8092	130930	383971

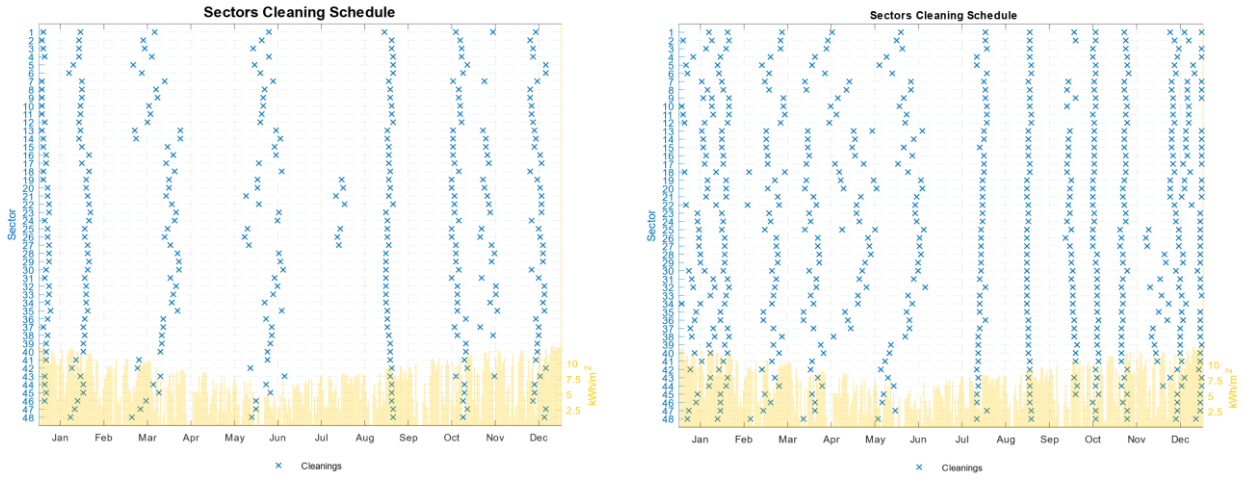
469



a) b)

470 *Figure 9. Cleaning schedule – Woomera - "owned trucks": a) lowest dust concentration (x 0.5) ; b) highest dust concentration (x10)*

471



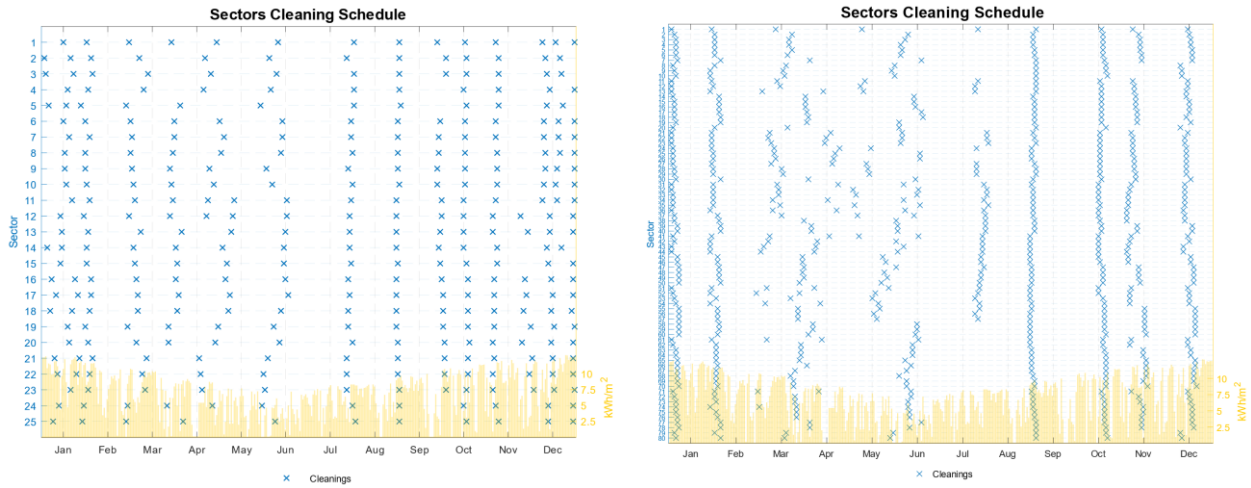
a) b)

Figure 10. Cleaning schedule – Woomera - "on call": a) low electricity price (- 50%) ; b) high electricity price (+ 50%)

5.1.2 Solar field sectorizations

The size and the number of the sectors through which the solar field has been divided to perform the optimization of the cleaning schedule have been chosen according to the reasons explained in Section 4. However, for the sake of completeness, it is worth considering that technological and design constraints or the exploitation of different cleaning technologies could lead to higher or lower cleaning speeds, as well as cleaning patterns that would impose a different configuration of the sectors. The impact of these aspect on the cleaning optimization is assessed hereafter.

To evaluate the effect of the cleaning speed on the optimal cleaning schedule, the extremes of the range proposed by Pfahl et al. (2017) have been adopted for the "on call" scenario: the maximum value is 3750 m^2/h and the minimum value is 1250 m^2/h. The corresponding number of sectors whose area equals one truck daily cleaning capability is about 25 (5 radial and 5 angular partitions) and 80 (10 radial and 8 angular partitions), respectively. Although it is expected that higher cleaning speeds would incur higher costs per square meter (or lower cleaning effectiveness), the same economic assumption reported in Table 2 are applied since a detailed modelling of the relationship between cost/cleaning speed and cleaning effectiveness is outside the scope of this study. As reported in Table 10, the higher cleaning speed results in a lower TTC since the heliostats can be cleaned more often with low extra cost while a lower cleaning speed sensibly increases the TTC since an higher number of cleaning shifts is required to maintain the optimal soiling factor. The optimal cleaning schedule for each of the two considered cleaning speeds is depicted in Figure 11.



a) b)

Figure 11. Cleaning schedule – Woomera - "on call": a) high cleaning speed ; b) low cleaning speed

Finally, two additional sectorial configurations are considered, changing the number of radial and angular partitions of the solar field while keeping the same number of heliostats per sector (and hence total number of sectors). The analysis is performed only on the "on call" case for the location of Woomera. The variation of the total cleaning cost obtained through the MILP model for these two configurations with respect to the base case is reported in Table 10. The results are very similar to the base case, however the TCC slightly increases when adopting unbalanced sectorizations (i.e. much higher/lower number of radial vs angular partitions). This is due to the higher error made by assuming the whole sector to behave (in terms of soiling factor and optical efficiency) as its representative heliostat (highlighted by red dots in Figure 12). Finally, the computational time for each case is also reported in Table 10. It can be noted that as the number of sectors increases, so does the time required to run the optimization.

Table 10. Sectorization analysis outcomes

Sectors (Radial x Angular)	Cleaning Speed [m^2/h]	TCC [k$]	ΔTCC [k$]	ΔTCC [%]	Number of Cleanings	Computational time [s]
6 x 8 (base case)	2000	1348.0	-	-	526	425087
10 x 8	1250	1682.5	334.5	24.82%	698	750911
5 x 5	3750	1041.1	-306.9	-22.77%	341	53201
16 x 3	2000	1348.6	0.6	0.04%	519	391880
2 x 24	2000	1349.2	1.2	0.09%	520	537412

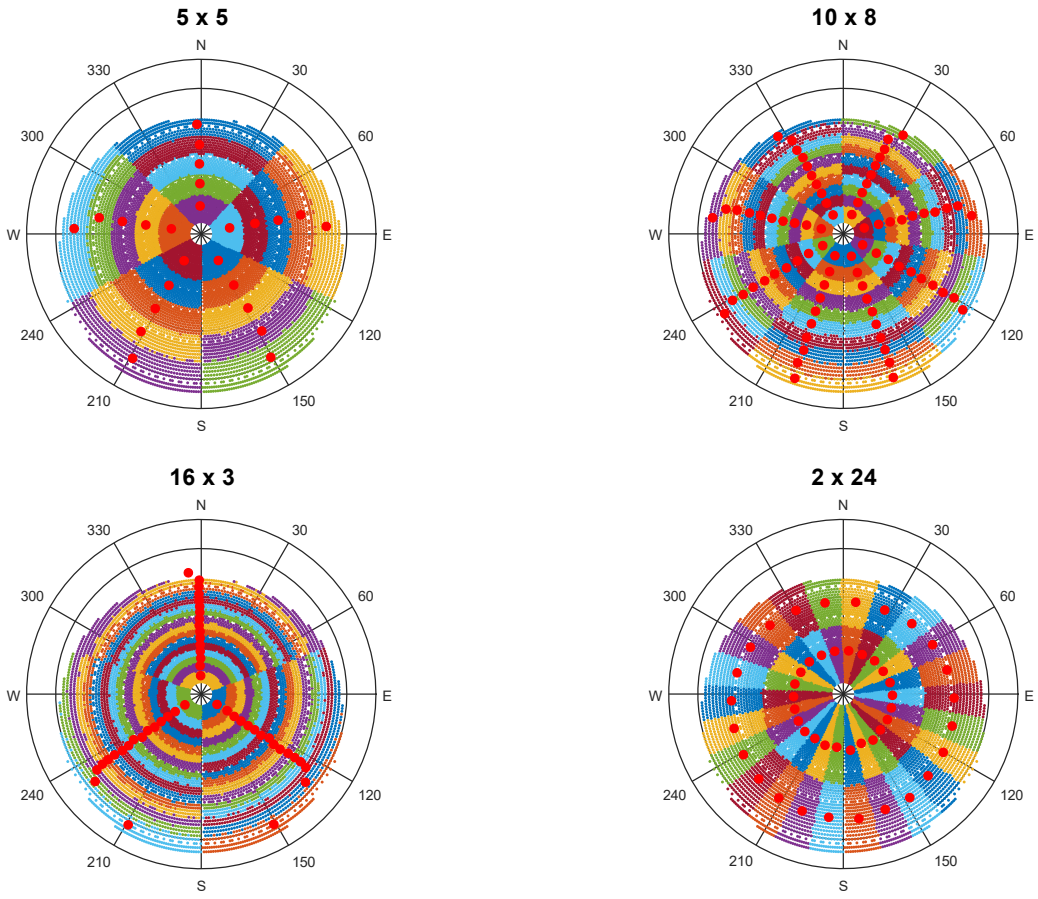


Figure 12. Solar field sectorizations

6 Conclusions

The most suitable sites for the deployment of ST plants are usually arid and desert areas, where the available DNI is very high and precipitations are low, while dust or sand events are frequent. These environmental conditions are likely to cause significant reduction of the optical efficiency of the heliostats composing the solar field, hence reducing the power generation. The resulting lower profits in turn would hinder the ST plants competitiveness in the energy market. Artificial cleaning of the solar field is then mandatory to improve the productivity of a ST plant. The optimization of the cleaning activities is fundamental to achieve better performance and to lower the Levelized Cost of Electricity. This paper presented the development of an innovative optimization method of heliostat cleaning strategies through a Mixed Integer Linear Programming (MILP) model. The optimization relies on a validated physical model for solar collectors soiling which provides the optical efficiency losses in the different sectors of the solar field: the outcomes of the soiling model depict a very inhomogeneous optical efficiency loss around the solar field, which further states the relevance of a cleaning scheduling that properly considers the different and time-varying cleaning frequency for each sector of the solar field. The developed algorithm maximizes the revenues of a ST plant by minimizing the costs related to cleaning activities and soiling losses. In addition, a simple heuristic optimization is proposed and compared to the results achieved with the MILP model.

For the base case of Woomera analysed in this study, the results of the optimization show a significant potential for reduction of the total cleaning costs up to 15% in the “on call” scenario, which corresponds to 1.35 M$ per year. It is

important to point out that this cost reduction is achieved without any additional investment but just taking advantage of the optimized cleaning strategies.

The optimization of the cleaning strategies has been applied to two different plant locations with different environmental characteristics in terms of dust concentration and radiative power availability. A sensitivity analysis with regards to airborne dust concentration, electricity price, cleaning speed, and sectorial configuration has finally been performed to prove the strengths of the MILP model and the importance of the cleaning activities in ST plants, giving a remarkable insight of their potential optimization and cost reduction. The results also demonstrate that the economic impact of cleaning is relevant in terms of overall revenues of the plant and hence on the LCOE.

Future studies will focus on the refining of the economic model featuring a comparison between different cleaning technologies coupled with a more precise description of the actual O&M cost structure, and on the extension of the optimization algorithm to include the number and the shape of the sectors as variables.

Acknowledgements

G. Picotti, M.E. Cholette, G. Manzolini, and T. Steinberg acknowledge the support of the Australian Government for this study, through the Australian Renewable Energy Agency (ARENA) within the framework of the Australian Solar Thermal Research Institute (ASTRI – Project ID P52).

The authors also acknowledge the Office of Environment and Heritage (OEH) of New South Wales for providing environmental data required for the optimizations.

References

Ashley, T., Carrizosa, E., Fernández-Cara, E., 2019. Heliostat field cleaning scheduling for Solar Power Tower plants: A heuristic approach. Appl. Energy 235, 653–660. https://doi.org/10.1016/j.apenergy.2018.11.004

Astolfi, M., Binotti, M., Mazzola, S., Zanellato, L., Manzolini, G., 2016. Heliostat aiming point optimization for external tower receiver. Sol. Energy. https://doi.org/10.1016/j.solener.2016.03.042

Bergeron, K.D., Freese, J.M., 1981. Cleaning Strategies for Parabolic-Trough Solar-Collector Fields; Guidelines for Decisions, Sandia National Laboratories.

Binotti, M., Astolfi, M., Campanari, S., Manzolini, G., Silva, P., 2017. Preliminary assessment of sCO<inf>2</inf>cycles for power generation in CSP solar tower plants. Appl. Energy 204. https://doi.org/10.1016/j.apenergy.2017.05.121

Fathi, M., Abderrezek, M., Grana, P., 2017. Technical and economic assessment of cleaning protocol for photovoltaic power plants: Case of Algerian Sahara sites. Sol. Energy 147, 358–367. https://doi.org/10.1016/j.solener.2017.03.053

Fernández-García, A., Álvarez-Rodrigo, L., Martínez-Arcos, L., Aguiar, R., Márquez-Payés, J.M., 2014. Study of different cleaning methods for solar reflectors used in CSP plants. Energy Procedia 49, 80–89. https://doi.org/10.1016/j.egypro.2014.03.009

Guorobi Optimization, L., 2018. Gurobi Optimizer Reference Manual [WWW Document].

IRENA, IEA-ETSAP, 2013. Concentrating solar power, Technology Brief. https://doi.org/10.1063/1.2993731

IRENA Secreteriat, Crespo, L. (ESTELA), Dobrotkova, Z. (IEA), Philibert, C. (IEA), Richter, C. (DLR), Simbolotti, G. (ENEA), Turchi, C. (NREL), Wenhua, X. (UNIDO-I., 2012. Concentrating Solar Power, Renewable Energy Technologies: Cost Analysis Series, Insights. https://doi.org/10.1063/1.2993731

Jones, R.K., Baras, A., Saeeri, A. Al, Al Qahtani, A., Al Amoudi, A.O., Al Shaya, Y., Alodan, M., Al-Hsaien, S.A., 2016. Optimized Cleaning Cost and Schedule Based on Observed Soiling Conditions for Photovoltaic Plants in Central Saudi Arabia. IEEE J. Photovoltaics 6, 730–738. https://doi.org/10.1109/JPHOTOV.2016.2535308

Kutscher, C., Mehos, M., Turchi, C., Glatzmaier, G., Moss, T., 2010. Line-Focus Solar Power Plant Cost Reduction Plan.

Larrayoz, A.M., Schöttl, P., Leonardi, E., Les, I., Rohani, S., Pisani, L., 2019. Techno-economic heliostat field optimization: Comparative analysis of different layouts. Sol. Energy 180, 601–607. https://doi.org/10.1016/j.solener.2019.01.053

Lofberg, J., 2004. YALMIP : a toolbox for modeling and optimization in MATLAB. 2004 IEEE Int. Conf. Comput. Aided Control Syst. Des. 284–289. https://doi.org/10.1109/CACSD.2004.1393890

Manzolini, G., Binotti, M., Bonalumi, D., Invernizzi, C., Iora, P., 2019. CO 2 mixtures as innovative working fluid in power cycles applied to solar plants. Techno-economic assessment. Sol. Energy 181, 530–544. https://doi.org/10.1016/j.solener.2019.01.015

Mehos, M., Turchi, C., Vidal, J., Wagner, M., Ma, Z., Ho, C., Kolb, W., Andraka, C., Kruizenga, A., 2017. Concentrating Solar Power Gen3 Demonstration Roadmap, Nrel/Tp-5500-67464. https://doi.org/10.2172/1338899

NREL, 2017. Solar pilot [WWW Document].

NREL, 2014. System Advisory Model [WWW Document].

584 Ortigosa, P.M., Redondo, J.L., Berenguel, M., Álvarez, J.D., Cruz, N.C., Salhi, S., 2018. Hector, a new
585 methodology for continuous and pattern-free heliostat field optimization. Appl. Energy 225, 1123–
586 1131. https://doi.org/10.1016/j.apenergy.2018.05.072

587 Pfahl, A., Coventry, J., Röger, M., Wolfertstetter, F., Vásquez-Arango, J.F., Gross, F., Arjomandi, M.,
588 Schwarzbözl, P., Geiger, M., Liedke, P., 2017. Progress in heliostat development. Sol. Energy 152, 3–
589 37. https://doi.org/10.1016/j.solener.2017.03.029

590 Picotti, G., Binotti, M., Cholette, M.E., Borghesani, P., Manzolini, G., Steinberg, T., 2019. Modelling the
591 soiling of heliostats: Assessment of the optical efficiency and impact of cleaning operations. AIP Conf.
592 Proc. 2126, 30043. https://doi.org/10.1063/1.5117555

593 Picotti, G., Borghesani, P., Cholette, M.E., Manzolini, G., 2017. Soiling of solar collectors - Modelling
594 approaches for airborne dust and its interactions with surfaces. Renew. Sustain. Energy Rev.
595 https://doi.org/10.1016/j.rser.2017.06.043

596 Picotti, G., Borghesani, P., Manzolini, G., Cholette, M.E., Wang, R., 2018. Development and Experimental
597 Validation of a Physical Model for the Soiling of Mirrors for CSP Industry Applications. Sol. Energy 173,
598 1287–1305. https://doi.org/10.1016/j.solener.2018.08.066

599 Polimeni, S., Binotti, M., Moretti, L., Manzolini, G., 2018. Comparison of sodium and KCl-MgCl<inf>2</inf>as
600 heat transfer fluids in CSP solar tower with sCO<inf>2</inf>power cycles. Sol. Energy 162.
601 https://doi.org/10.1016/j.solener.2018.01.046

602 Salomé, A., Chhel, F., Flamant, G., Ferrière, A., Thiery, F., 2013. Control of the flux distribution on a solar
603 tower receiver using an optimized aiming point strategy: Application to THEMIS solar tower. Sol.
604 Energy 94, 352–366. https://doi.org/10.1016/j.solener.2013.02.025

605 Sánchez-González, A., Santana, D., 2015. Solar flux distribution on central receivers: A projection method
606 from analytic function. Renew. Energy 74, 576–587. https://doi.org/10.1016/j.renene.2014.08.016

607 Sanchez, M., Romero, M., 2006. Methodology for generation of heliostat field layout in central receiver
608 systems based on yearly normalized energy surfaces. Sol. Energy 80, 861–874.

609 Sarver, T., Al-Qaraghuli, A., Kazmerski, L.L., 2013. A comprehensive review of the impact of dust on the use
610 of solar energy: History, investigations, results, literature, and mitigation approaches. Renew. Sustain.
611 Energy Rev. 22, 698–733. https://doi.org/10.1016/j.rser.2012.12.065

612 Seinfeld, J.H., Pandis, S.N., 1998. Atmospheric chemistry and physics: from air pollution to climate change.
613 Wiley-Interscience, New York.

614 SolarReserve, n.d. https://issuu.com/solarreserve/docs/solarreserve_crescentdunes-brochure [WWW
615 Document].

616 Terhag, F., Wolfertstetter, F., Wilbert, S., Hirsch, T., Schaudt, O., 2019. Optimization of cleaning strategies
617 based on ANN algorithms assessing the benefit of soiling rate forecasts, in: SOLARPACES 2018. p.
618 220005. https://doi.org/10.1063/1.5117764

619 Truong Ba, H., Cholette, M.E., Wang, R., Borghesani, P., Ma, L., Steinberg, T.A., 2017. Optimal condition-
620 based cleaning of solar power collectors. Sol. Energy 157, 762–777.
621 https://doi.org/10.1016/j.solener.2017.08.076

622 Wang, Z.H., Xu, Z.G., 2018. Optimal Cleaning Schedule of Photovoltaic Module, in: 2018 IEEE IEEM. pp.
623 1637–1641.

624 Wolfertstetter, F., Wilbert, S., Dersch, J., Dieckmann, S., Pitz-Paal, R., Ghennioui, A., 2018. Integration of
625 soiling-rate measurements and cleaning strategies in yield analysis of parabolic trough plants. J. Sol.
626 Energy Eng. 140. https://doi.org/10.1115/1.4039631

627

628