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Maintenance Optimization of Parabolic Trough Power Plants Through a Lifetime Simulation Model Validated with Five-Years of Operational Data

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Abstract. Modelling and Simulation of Concentrated Solar Power (CSP) plants is a crucial requirement for future growth and improvement of the technology. In this paper, the development of a functional and reliable model of a Parabolic Trough Collector (PTC) power plant is presented and validated with existing five-year operational data of a 50 MW_{el} plant equipped with seven hours full load thermal storage, located in Spain. A mean absolute error of 2.53% between the simulation and plant data was found when considering net energy generated over the five-year period. Subsequently, an optimized maintenance plan is proposed, and the plant behavior is forecasted. The new maintenance strategy is developed to optimize the mirrors current cleaning schedule, thereby mitigating significant detrimental soiling effects on the optical efficiency while reducing water and fuel consumption. Results show an increase in solar gain by 0.46% and reductions in water usage and fuel consumption by 22.1% and 22.3%, respectively.

Keywords: Concentrated Solar Power, Modelling and Simulation, Operation and Maintenance

1. Introduction

Due to its energy dispatchability and competitive Levelized Cost of Electricity (LCOE) CSP is considered highly relevant in the future of renewable energy systems. The integration of low-cost thermal energy storage enables plants to deliver reliable and stable power over extended periods. Among CSP technologies, PTC is considered as the most mature and widely adopted variant, with a world installed capacity of 5.5 GW representing more than 85% share of the overall CSP capacity [1]. To further accelerate the growth of the technology, it is essential to have a reliable modelling framework to accurately simulate the performance of the plant throughout its operational years. This framework is crucial for optimizing the plant's performance across various aspects of its operation.

As part of the German project SmartCSP, Fraunhofer ISE contributes to this goal by developing reliable CSP models for assessing annual yields in techno-economic evaluations and additionally testing control and operation strategies [2]. This study analyses five-year experimental data of a 50 MW_{el} PTC power plant, with the aim of increasing model accuracy and exploring optimized operation and maintenance strategies.

The most suitable sites for the deployment of CSP plants are usually arid and desert areas, where the available Direct Normal Irradiance is very high and precipitations are low, while dust or sand events are frequent. These environmental conditions are likely to cause significant reduction in the optical efficiency of the mirrors in the solar field, hence reducing the power generation. The resulting lower profits in turn would hinder the CSP plants competitiveness in the energy market. To counter these challenges, effective cleaning of the solar field is then mandatory to improve the productivity of a CSP plant. In this paper, an optimization on the current cleaning strategies used by the PTC plant is performed. This optimization is a fundamental step to properly balance the plant's Operation and Maintenance (O&M) costs with the revenue losses caused by soiled mirrors.

2. Methodology

For the simulations, the Fraunhofer ISE inhouse dynamic system simulation tool, ColSim is used [3]. The first part of the study analyzes and implements the experimental data and operating strategies of the CSP plant into our model to further increase its accuracy. Design parameters as well as local environmental conditions from the site are considered as inputs. Based on the ColSim model, an annual comparison of energy yield between the simulation and operational plant data from 2017-2021 is performed.

Additionally, new cleaning strategies are developed to optimize the current mirror cleaning schedule of the solar field. First, the five years of cleaning records are input to create a reference system with the measured distribution of cleanliness across the different subfields. Second, the optimal cleaning schedule is determined considering the economics of cleaning activities, namely fuel and water consumption, similar to Rohani et al. [4] or the solar tower system approach discussed by Picotti et al. [5]. The optimization aims to maximize the yearly plant revenue, or equivalently to minimize the combined costs of yearly cleaning for O&M along with expenses associated with energy loss due to soiled mirrors.

The defined reference system employed in this study is a 50 MW_{el} solar thermal power plant with 7.5 hours of full load thermal storage located in southern Spain. The solar field consist of 152 loops of Euro Trough PTCs orientated north south, with a total aperture area of 497,040 m^2. The set point temperature for the solar field outlet is 393°C, with Therminol® VP-1 as Heat Transfer Fluid (HTF). The receiver tubes were supplied by the Schott Company with the model "Schott PTR 70".

The storage system is an indirect two-tank configuration for molten salt storage, with a heat exchanger between the two tanks used for HTF heating or cooling. The power block consists of a solar steam generator, seven stages of steam turbines, low and high-pressure feed-water heaters, deaerator, condenser, and condensate and feed-water pumps. Figure 1 shows a simplified plant layout.

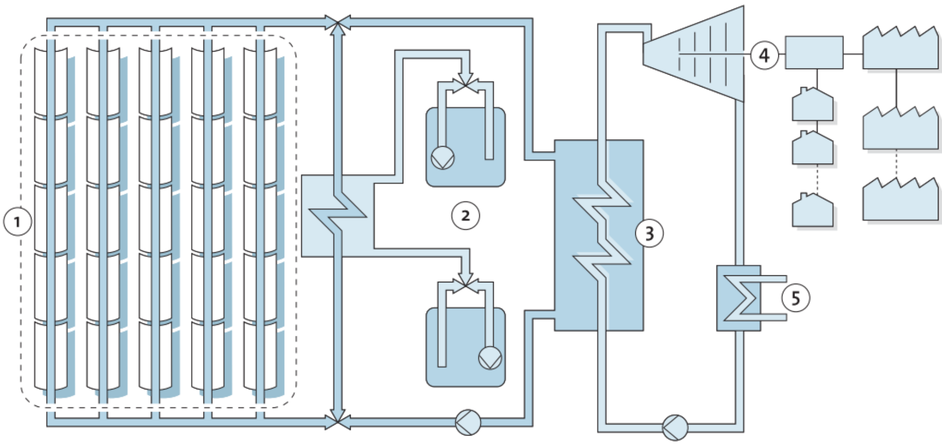

Figure 1. *Schematic plant representation [6]. (1) Solar Field (2) Indirect Thermal Storage (3) Heat Exchanger (4) Power Block (5) Condenser.*

3. Model Description

ColSim is a dynamic system simulation tool that applies a plug flow principle to perform complex dynamic system simulations in variable timesteps. The model includes thermal and optical evaluation of the solar collector field taking into consideration characteristics as the geometry and setup of the solar field, controlled mass flows and environmental conditions. The model includes both thermal and optical evaluations at the individual Solar Collector Assembly (SCA) level, accounting for optical losses such as shading, soiling, cosine effect, and end losses, as well as thermal and defocusing losses. Furthermore, the performance of a two-tank heat storage using molten salt, pumps, heat exchangers and a power block are included in the plant model for the completeness of the system. Parameters used for the reference plant simulations are described in Table 1.

Table 1. *Main design parameters for simulation in ColSim.*

Parameter	Input
Collector Model	EuroTrough ET-150
Plant Distribution	152 loops with 4 SCA each.
Solar Field Design Temperatures	293 - 393 °C
Heat Transfer Fluid	Therminol – VP1
Storage Capacity	7.5 full load hours
Storage Medium	Molten Salt ($NaNO_3$ 60% / KNO_3 40%)
Storage Temperatures	260 - 390 °C
Nominal Power	50 MW

As the solar field performance is the primary emphasis of this study, the solar field model is further described in detail. Each component consists of one or several nodes representing spatial discretization. For each node, the solar heat gain Q_{gain} is calculated based on the subtraction of absorbed energy Q_{solar} minus thermal losses Q_{loss} like shown in Figure 2.

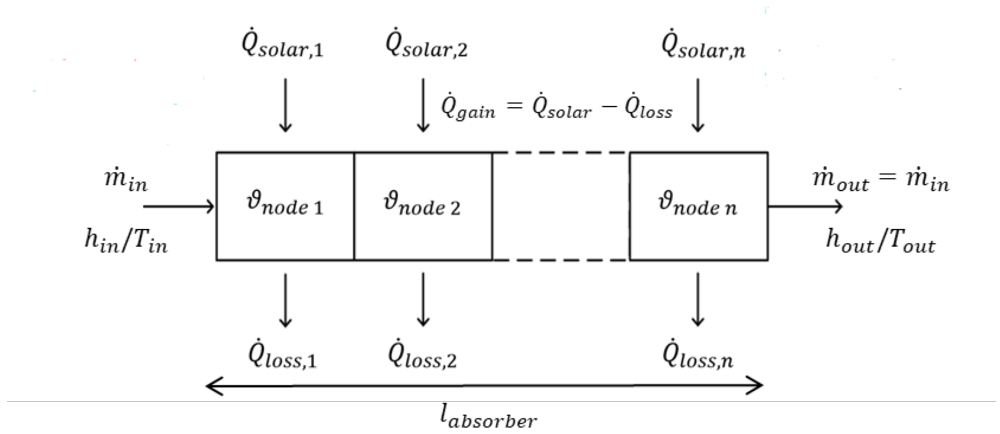

Figure 2. *Simplified discretized Solar Field model*

First, the absorbed power Q_{solar} is calculated with equation 1, based on the optical efficiency defined in equation 2:

$$Q_{solar} = A_{ap} \cdot G \cdot \eta_{opt} \cdot f_c \tag{1}$$

$$\eta_{opt} = \eta_0 \cdot IAM \cdot cos\theta i \cdot f_{el} \cdot f_{rs} \tag{2}$$

where A_{ap}: Aperture Area (m^2), G: Direct Normal Irradiation (W/m^2), η_{opt}: Optical Efficiency, fc: Cleanliness Factor, η_0: Peak Optical Efficiency, IAM: Incidence Angle Modifier, θi: Incidence Angle, f_{el}: End Loss Factor and f_{rs}: Row Shading.

The final heat gain Q_{gain} to the HTF includes reduction by defocusing. This phenomenon usually occurs in summer when the potential irradiation threatens to exceed the limit fluid temperature. For the thermal losses the third-order correlation published by Schott in PTR 70 receiver data sheet for temperatures higher than 250°C [7] is used and summarized as follows:

$$Q_{loss} = 5E^{-6} \cdot T^3{}_{abs} - 1E^{-3} \cdot T^2{}_{abs} + 9.921E^{-1} \cdot T_{abs} \tag{3}$$

Where Q_{loss} is the specific absorber heat losses in W/m and T_{abs} is the absorber temperature in °*C*. This thermal loss equation is applicable to a perfectly vacuum receiver. However, its applicability to all operational conditions is still under investigation. Further analyses of specific cases and their corresponding coefficients are ongoing and will be incorporated into future simulations. Another important parameter that will be further used for the comparison between plant data and simulation is the solar field's overall thermal efficiency ($\eta_{th,SF}$), and it can be expressed as:

$$\eta_{th,SF} = \frac{Q_{solar} - Q_{loss}}{G \cdot A_{ap}} \tag{4}$$

Additionally, ColSim employs a collector-wise approach, enabling to simulate independent cleanliness values for each SCA in the solar field. This approach enables a more detailed discretization of cleanliness, offering a more accurate representation of real plant conditions and performance. This refined model is further used to introduce specific cleanliness values for each individual collector, provided by plant data, enhancing the precision of the simulation results, and capturing the spatial variability across the solar field.

4. Model Validation

In this study, plant behavior for a five-year period was simulated, with a primary focus on assessing solar field production capacity and power output. Average cleanliness values per subfield, shown in Table 2, were incorporated in the modelling from the start, as emphasized by Rohani et al. [4] where the relevance in a detailed model was stated. Annual accumulated solar gains and net power from 2017 to 2021, provided by ColSim and operational plant data are shown in Figure 3a.

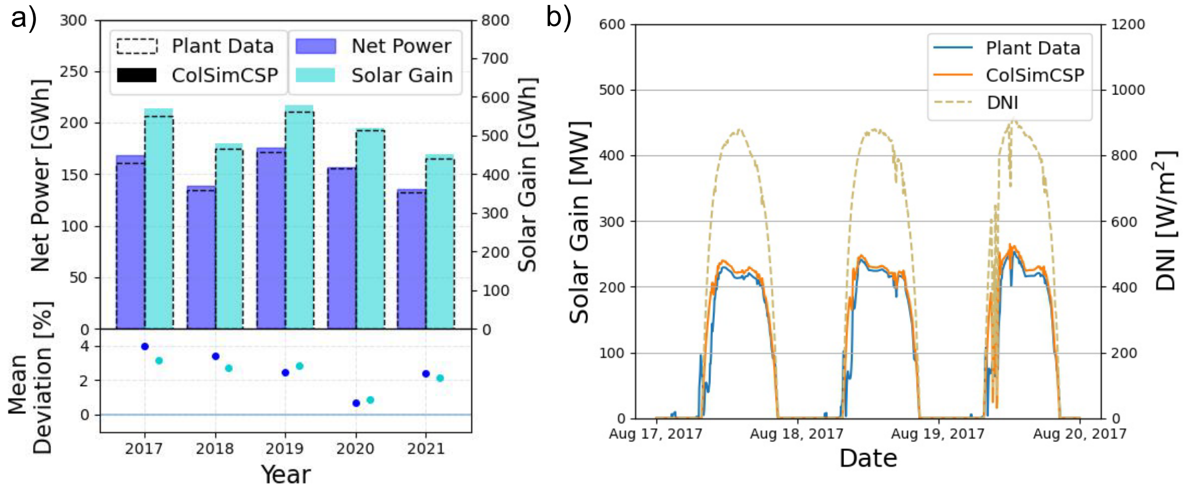

Figure 3. *Validations between plant data and ColSim simulations for a) annual accumulated ColSim solar gains and net power and b) three-day solar gain simulations in August 2017.*

Table 2. *Subfield cleanliness average per year.*

Subfield	2018	2019	2020	2021
SE	0.961	0.962	0.967	0.957
SW	0.967	0.966	0.965	0.961
NE	0.962	0.962	0.960	0.958
NW	0.964	0.959	0.964	0.957

Furthermore, their deviations, as well as a detailed solar gain simulation for three days in 2017 in comparison to the measured plant data are shown in Figure 3b. Deviations in the range of 1-4% over the five-year period were found, representing model's reliability. By incorporating cleanliness values that vary throughout the year, the simulations can capture the dynamic interaction between maintenance and performance, leading to accurate and realistic results.

5. Maintenance Optimization

A collector-wise soiling analysis was conducted over a 15-day period, from September 16th to 30th 2019, selected due to the availability of individual SCA temperature data. Cleaning operations were limited to weekdays and subject to plant conditions, resulting in five days without cleaning. Figure 4 illustrates the average cleanliness distribution per SCA given by plant data during this 15-day period, yielding a solar field average of 95.68%. Each cell in the heatmap represents a single SCA, and four together form one loop. The color intensity reflects the cleanliness, where darker tones indicate higher levels of soiling. The solar field is divided into four subfields: Northwest (NW), Northeast (NE), Southwest (SW), and Southeast (SE).

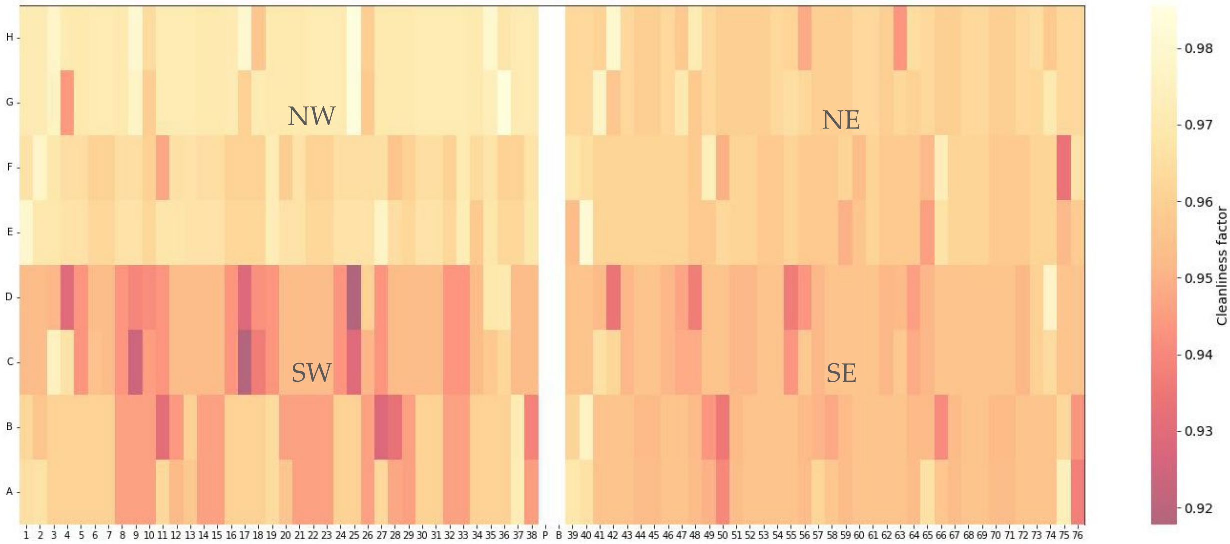

Figure 4. *Representation of the Solar Field average cleanliness values per SCA for a 15-day period in September 2019.*

The inhomogeneous distribution of cleanliness across the loops, visible in Figure 4 as the darker red regions, negatively impacts the solar gain and outlet temperature of the subfields, leading to reduced thermal efficiency and a decrease in the net power output of the plant [4]. These impacts highlight the need to implement a more effective cleaning strategy, such as one that prioritizes fewer but more strategically chosen SCAs.

To address this, the proposed model implements a selective, resource-constrained cleaning strategy that prioritizes collectors based on their cleanliness levels. The model is designed to balance cleaning efficiency with resource constraints, optimizing for water consumption while prioritizing the high soiling areas. As illustrated in Figure 5, the algorithm begins by reading cleanliness data for each collector and assigning priorities to each loop based on predefined thresholds for the respective cleaning technology. It then dynamically adjusts the cleaning process using real-time data and established operational limits, targeting lower resource consumption. A cleaning schedule is generated that details the number of loops to be cleaned, the subfields they belong to, and the specific technology (spray or brush) to be used. This allows for a clear, data-driven plan for daily cleaning operations, instead of a fixed cleaning schedule, ensuring that operations are both efficient and responsive to changing conditions.

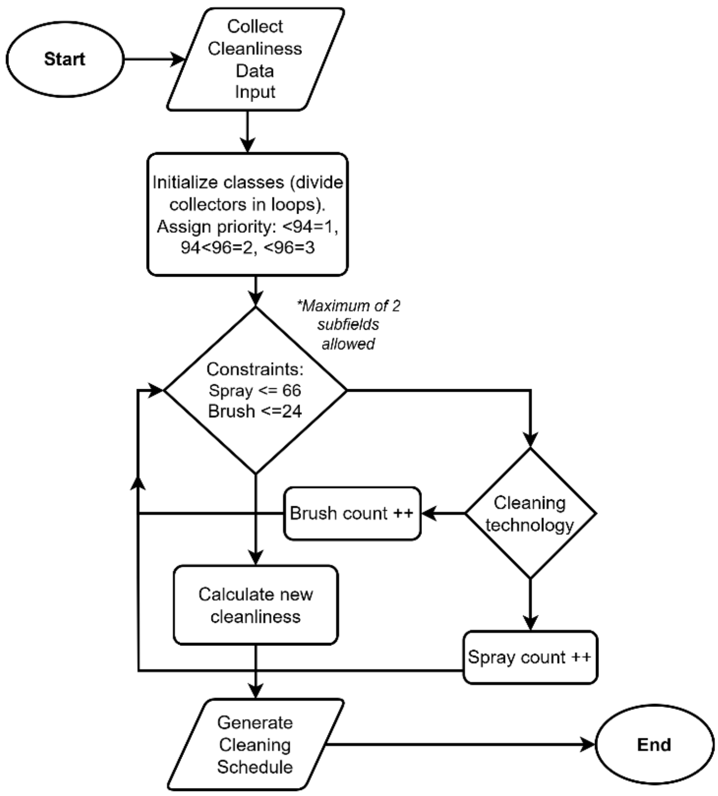

Figure 5. *Simplified flowchart of the data-driven cleaning schedule under resource constraints.*

To ensure efficient use of cleaning resources, the process is constrained by the daily maximum number of SCAs cleaned with the spray method (66 SCAs) or the brush method (24 SCAs). These values were primarily determined by their associated water consumption. For example, current cleaning of 76 SCAs with the spray method requires 34,000 liters of water. Given that each truck has a capacity of 10,000 liters, the limit was set at 66 SCAs to reduce the need for truck refills from four to three. Similarly, cleaning 44 SCAs with brushes requires 18,000 liters of water, so the limit was reduced to 24 SCAs, thereby lowering the water consumption to one truckload.

In addition, the cleaning is limited to a selected maximum of two subfields per day, each using a different cleaning technology. This approach reduces truck travel distances to create a more practical and efficient framework. The incorporation of flexible resource allocation, based on real-time data and operational constraints, further enhances the system's overall feasibility and reliability in practice.

6. Results

By optimizing the cleaning strategy to target only the most critical sections, water and fuel consumption can be reduced, along with the number of SCAs cleaned. Applying the previously described method to the same 15-day period in September results in a more uniform cleanliness distribution across the solar field. This is illustrated in Figure 6, which presents the average cleanliness per collector following optimization, yielding an improved solar field average of 96.24%.

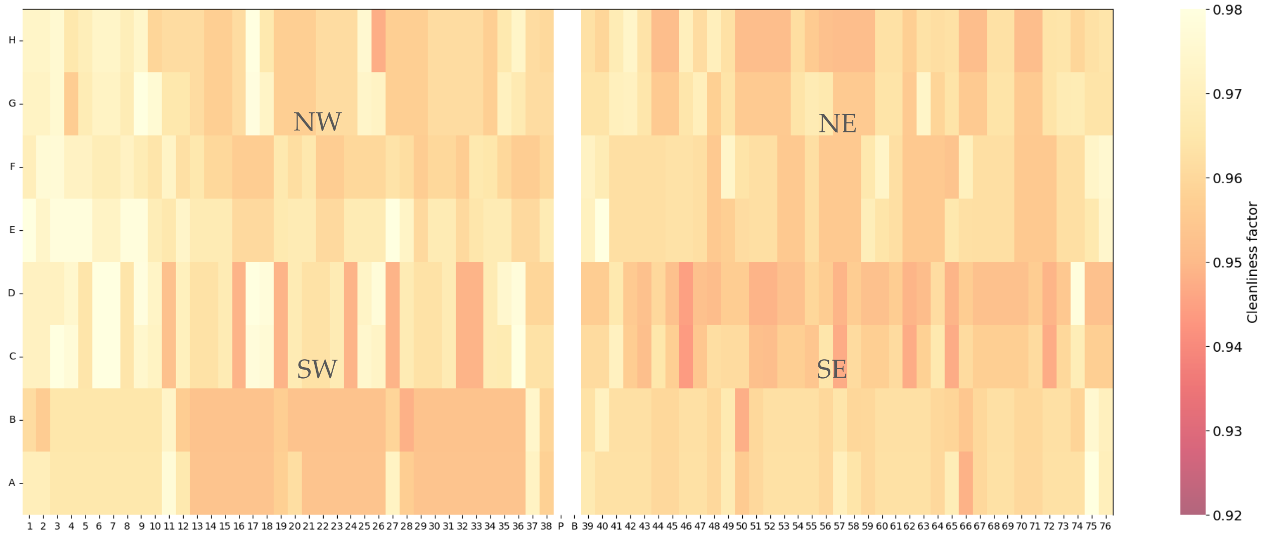

Figure 6. *Representation of the Solar Field average cleanliness values per SCA after selective cleaning for a 15-day period in September 2019.*

Subsequently, a detailed collector-wise simulation was conducted in ColSim over the 15-day period. Each collector was assigned a daily cleanliness value according to the selected cleaning strategy. Two simulation scenarios were evaluated: the current cleaning schedule, which used cleanliness values from Figure 4, and the selective cleaning strategy, which was based on the optimized values represented in Figure 6. This last strategy not only conserves resources but also enhances overall system performance as showcased in Table 3. Where, power output and solar gain increased by 0.46% and 0.38%, respectively, while the average cleanliness of the solar field improved by 0.59%. In contrast, water and fuel consumption decreased by approximately 22% due to the reduced number of SCAs cleaned.

Table 3. *15-day performance details on current and optimized cleaning schedule.*

Parameter	Current cleaning	Selective cleaning	Mean difference
Average cleanliness	95.68	96.24	0.59%
No. SCA cleaned (Brush)	396	240	-39.39%
No. SCA (Spray)	760	660	-13.16%
Water (m^3)	505	393.35	-22.11%
Fuel (liters)	3636	2823.60	-22.34%
Solar gain (MW)	263,130.25	264,336.36	0.46%

While resource reduction, in particular water-saving thresholds, was the primary constraint in the study, the simulations also indicated that the proposed cleaning schedule preserved power output at a stable level throughout the evaluation period. As a next step, the method will be further tested to determine the minimum cleaning effort required without compromising power output over extended periods and across the entire plant.

7. Conclusion

The validation of the internal system simulator ColSim was completed using five-year operational data from a $50MW_{el}$ reference plant in Spain. The model presents a high accuracy with a measured mean absolute error of 2.53% over the five-year period. A key feature of the model is its ability to simulate performance at the collector-wise level, enabling a detailed assessment of individual SCAs across the solar field. Following validation, ColSim was employed to evaluate current plant performance against a proposed maintenance optimization strategy.

The study introduced an optimization method for cleaning strategies through a selective control, aiming to clean specific sectors on the plant using the validated collector-wise physical model. The results highlight the relevance of a cleaning schedule that properly considers the different and time-varying cleaning frequency for each sector of the solar field and how this targeted cleaning efforts can effectively reduce overall O&M demands while minimizing water consumption, a critical factor in arid regions where CSP plants are typically located. During the 15-day simulation period in September, water and fuel consumption decreased by approximately 22% due to the reduced number of SCAs cleaned. Future work aims at extending this detailed analysis to calculate the potential benefits over longer periods.

In conclusion, the maintenance optimization of CSP plants requires a comprehensive approach that considers the inhomogeneous distribution of soiling, the importance of balanced soiling, and the implementation of strategic and real-time control measures for cleaning. By focusing on selective control and economic optimization, plants can enhance their operational efficiency, reduce maintenance costs, water and fuel consumption, and increase overall profitability. Additional work is needed on refining predictive models for soiling and exploring advanced cleaning technologies that further reduce the environmental and economic impact of maintenance activities.

Data availability statement

The operational data used for validating the system simulation tool in this research paper was graciously provided by a commercial CSP-Power plant. While we have been granted permission to use this data for our analysis, we cannot to share it without explicit consent. Therefore, the raw data supporting the conclusions of this article cannot be made publicly available.

Author contributions

Sayra Gomez: Conceptualization, Visualization, Formal Analysis, Software, Methodology, Writing - Draft, Review and Editing. Shahab Rohani: Software, Methodology, Writing – Review & Editing. Nicholas Chandler: Software, Writing – Review & Editing. Peter Schöttl: Software, Writing – Review & Editing. Thomas Kraft: Supervision, Methodology, Writing: Review and Editing. Gregor Bern: Co-Supervision, Writing: Review and Editing, Resources, Funding Acquisition.

Competing interests

The authors declare that they have no competing interests.

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