Minimizing Water Consumption of a CSP Plant, by Using an Online Optimization Algorithm for Cleaning Decisions

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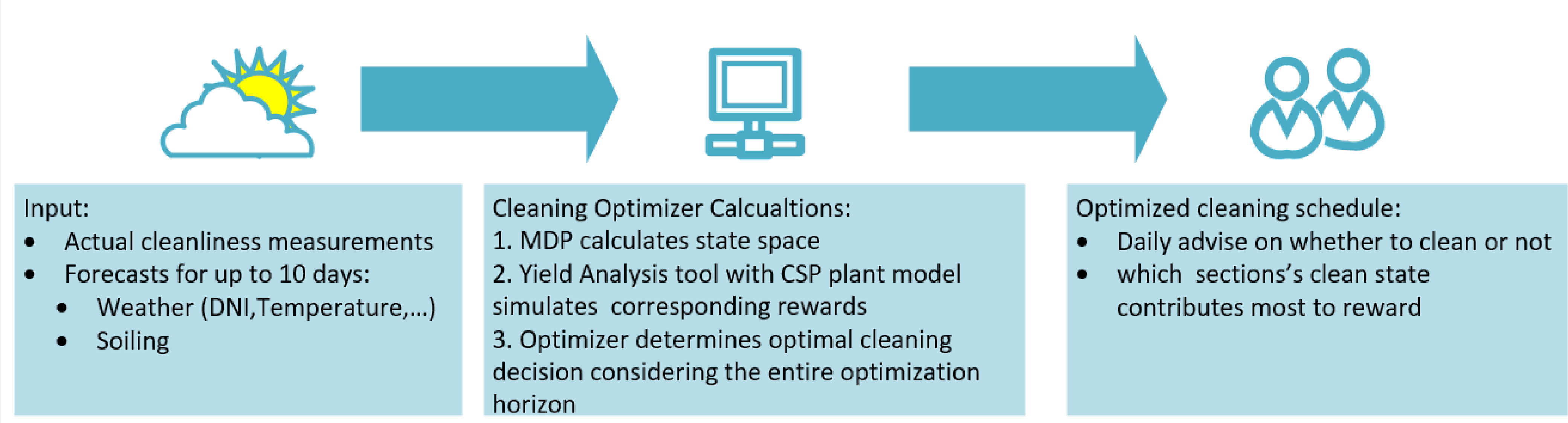

Figure 1) Online cleaning Optimization scheme

Introduction

Water is an increasingly scarce resource in some locations of existing CSP plants and new CSP plants are built in more arid regions. As a high cleanliness of CSP collectors is essential for high solar power efficiency and yield, a **tradeoff between water consumption for mirror cleaning and electricity generation** has to be addressed with cleaning schedules.

Previously a guideline to choose the optimal interval in a constant cleaning schedule had been developed in [1]. With the help of soiling rate measurements advanced cleaning strategies had been developed to improve site selection, the yield analysis and the resource assessment [2]. These developments had been enhanced based on artificial neural network algorithms to assess the benefit of soiling rate forecasts [3].

Within the SOLWARIS EU-project a soiling forecast model is developed, that combines dust forecasts and a soiling model to predict CSP mirror soiling for the upcoming three days [4,5]. This **soiling forecast will then be integrated in the first online cleaning scheduler** [6] which is presented within this poster. It offers an optimized cleaning schedule (with an optimization time horizon of 10 days) for a parabolic trough plant, that can be used by the operation staff to facilitate the everyday cleaning decision (see Figure 1). Therefore the optimizer makes use of the innovative information offered by soiling forecasting and soiling sensors [7].

Literature:

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Soiling in the Solar Field Model

The dependency of electricity generation of a CSP plant on the cleanliness of the solar field can not be expressed in one simple mathematical function. Instead it has to be calculated with a simulation model, as it

- depends on various parameters (solar Irradiation, temperatures…)
- relies on iterations
- is time dependent
- relies on operational decisions

An existing yield analysis tool is used to calculate the electricity generation of the CSP plant. A 50 MW_{el}-parabolic trough plant in southern spain with thermal storage and solar driven operation mode was set as reference plant for the first test of the cleaning optimizer.

The solar field model is adopted to make use of different cleanliness values for each loop i. The absorbed power $\dot{Q}_{abs,i}$ of each loop is the product of available thermal power by the sun $\dot{Q}_{avail,i}$, the nominal aperture area $A_{nom,i}$, a focus factor $f_{foc,i}$, optical efficiency $\eta_{opt,i}$ and cleanliness $\eta_{clean,i}$.

$$\dot{Q}_{abs,i} = A_{nom,i} \cdot \dot{Q}_{avail,i} \cdot \eta_{opt,i} \cdot \eta_{clean,i} \cdot f_{foc,i}$$

The cleanliness defines the ratio of the actual mirror reflectance $\rho_{actual,i}$ in comparison to the perfectly clean state ρ_{clean}.

$$\eta_{clean,i} = \frac{\rho_{actual,i}}{\rho_{clean}}$$

The rate at which the cleanliness changes over time is called soiling rate SR.

$$SR = \frac{\Delta\eta_{clean,i}}{\Delta t}$$

Using a SR forecast input, $\eta_{clean,i}$ of the upcoming days can be calculated and hence with the help of weather forecast data, the power generation of the upcoming days can be simulated. Each cleaning action sets the cleanliness back to 1 and comes along with a certain water consumption (defined by an empirical parameter).

The Optimization Problem

The optimization problem has the following specifications:

1. The impact of soiling on the energy production can not be described by a single function but requires a simulation model
2. cleaning the entire solar field takes at least a week. Hence the cleaning decision of one day does not only influence the energy output of this day, but also of the upcoming days. Therefore, the optimizer needs to consider different time steps simultaneously and the algorithm needs to optimize a sequence of decisions instead of a single one.
3. As the measurement of current space resolved cleanliness values is available, the solar field model is divided into section models
4. Forecasts for soiling and weather are only available for a short time horizon (around 3 days)

Markov Decision Process

To meet the described requirements, the concept of an online algorithm was chosen, which receives new information in each time step and hereupon adapts its decision process based on the new input. In [8,9] the concept of a Markov decision process was first introduced to formulate the problem of finding an optimal cleaning decision for CSP tower plants.

A Markov decision process describes the evolution of a system over a discrete time horizon. The system is influenced by a decision maker that can choose from different actions in each time step and thus initiates a change of the system.

The Markov decision process (Figure 2) can be represented by the tuple (S, A, p, r_S, V_0). For the optimizer we define this tuple as following:

- In the finite state space $\boldsymbol{S}$ each state s is represented by the cleaning configuration (cleanliness values of all sections of the solar field) and by the optimization period: $((\eta_1, \ldots, \eta_{10}), k)$
- The action space $\boldsymbol{A}$ consists of three different actions 'no cleaning', 'cleaning one set of loops' or 'cleaning two sets of loops'
- V_0 terminal reward function $V_0 : S \rightarrow \mathbb{R}$, that is obtained when the system reaches an end state, which is set to 0 for the model.

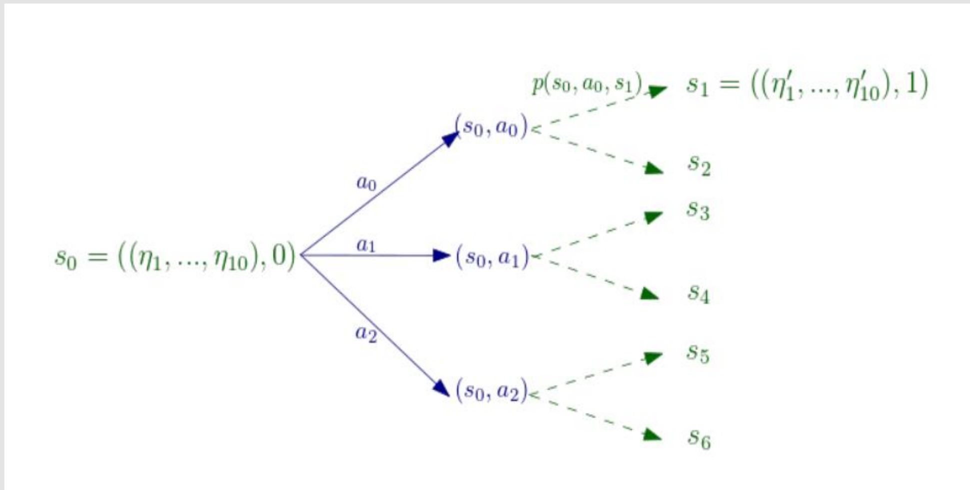

Figure 2) Markov Decision Process scheme [6]

- $\boldsymbol{p}$ is the transition probability $p : S \times A \times S \rightarrow [0,1]$ such that $\sum_{s' \in S} p(s, a, s') = 1$. Starting with a certain cleaning configuration and choosing a specific cleaning action we receive a new cleaning configuration in the next period based on the SR probabilities.
- $\boldsymbol{r_S}$ is the one-stage reward function $r_S : S \times A \times S \rightarrow \mathbb{R}$ This is where electricity generation $E_{el,s'}$ is weighted against water consumption. To avoid financial uncertainties at this stage of investigation, the alpha value α is introduced: a dimensionless parameter to decrease or increase the cost of the water consumption of a cleaning action

$$r_S(s, a, s') = E_{el,s'} - \alpha \cdot n_{cleaning}$$

with $n_{cleaning}$ being the number of cleaning actions.

The Optimizer uses a dynamic program to calculate an (optimal) sequence of decisions and then derive a decision for the current time step

➢ **The objective of the optimizer is, to maximize the reward ($E_{el} - \alpha \cdot n_{cleaning}$) of the entire optimization time horizon.**

Results

To improve the output of the optimizer, an evaluation of various parameters [6] had been performed on a simulation test bench with 6 months of empirical soiling and weather data. These are the results of the parameter study of the α-value (see Figure 3):

- Higher α-value » less cleaning
- Less cleaning » lower energy production (tradeoff line)
- No energy generation reduction at α = 2 and already up to 20% less cleaning
- Highest water saving (71%) for α = 10 » energy generation reduction of only 2%

The optimizer is able to forecast events of dumping and allows for a lower reflectance of the mirrors to save cleaning water consumption without significant reduction of energy generation.

In a next step the simulation model could be completed by an economic reward function with the water price as manipulated variable.

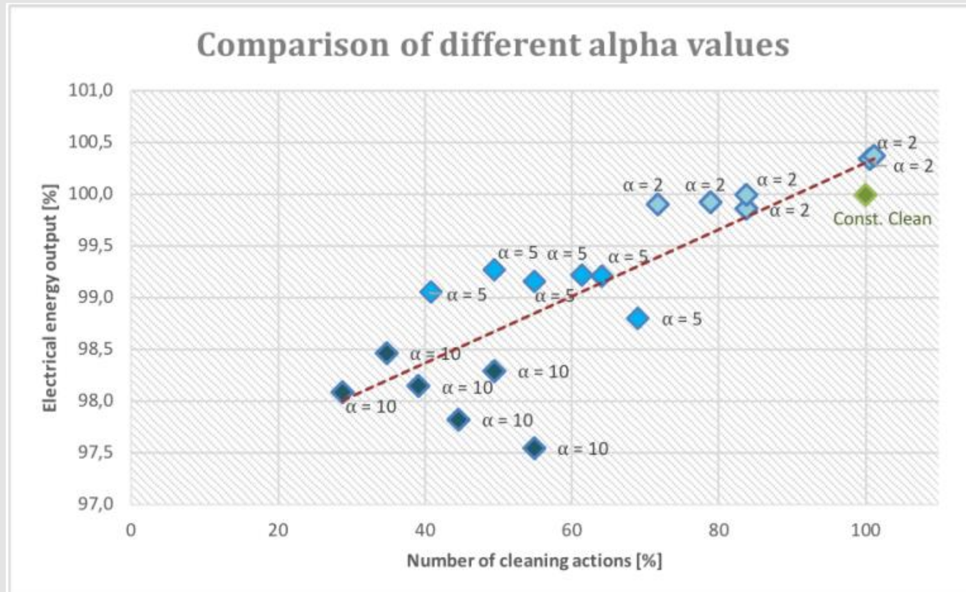

Figure 1) Simulation output for six SR Input sets and α-values 2, 5 and 10 compared to the output resulting from a constant cleaning schedule for the corresponding SR Input

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