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Modeling and simulation of the soiling dynamics of frequently cleaned reflectors in CSP plants

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ABSTRACT

The task of cleaning reflectors is a widely adopted strategy to handle the soiling in concentrated solar power (CSP) plants. The dynamics of the soiling of frequently cleaned mirrors is dependent on many factors such as the cleaning method, its frequency and the seasonal soiling rate. This study proposes a new approach to model the soiling of regularly cleaned reflectors instead of the inaccurate methods undermining the CSP yield by using fixed reflectance assumptions. Markov switching (MS) regime, which is a non linear time series approach where parameters are allowed to switch between the regimes, are applied on the reflectance data of second surface silvered-glass mirrors, exposed at the Plataforma Solar de Almería (PSA) in Spain during two years and cleaned biweekly using high pressure demineralized water. The nonlinearities typically exhibited by such reflectance time series are successfully modeled by accounting for two regimes, a soiled and a clean regime, and incorporating various parameters (rain, washing cycle, and lagged autoregressive terms) in the suggested MS models. Based on the information criteria and the diagnostic of the models residuals, the best model has a switching normalized reflectance mean of 0.944 during the clean regime versus 0.688 during the soiled regime, in addition to one fixed lag autoregressive term. In order to evaluate the adequacy of the proposed model versus the traditional approach, which uses fixed reflectance as input for estimating CSP plants yield, four reflectance scenarios were studied by simulating the output of a 30 MWe plant using TRNSYS© (TRaNsientSYstem Simulation) program. The first and the second scenarios used the time series of the measured and fitted model reflectance data, while the third and the forth scenarios used fixed inputs (a maximum and a yearly average reflectance). The comparison of the simulation results showed that adopting the innovative proposed concept of switching regimes results in very good performance, especially in the soiled regime during which the simplistic reflectance considerations, which ignore the soiling dynamics and the applied washing cycle, undermine the generated power.

1. Introduction

Due to their potential to produce renewable and cost effective energy, CSP projects, such as large CSP utility-scale plants (Mendelsohn et al., 2012), small-sized PTCs for industrial application (Fernández-García et al., 2015) or coupled CSP and desalination plants (Palenzuela et al., 2011), are promising options for clean energy production. Various candidate materials could be used in CSP plants, however the available supply of glass material (Pihl et al., 2012) and its high reflectance supports the deployment of glass based solar reflectors in the solar field of CSP plants.

Arid and semi arid locations with high Direct Normal Irradiance (DNI) are challenged by the degradation and persistent soiling of solar reflectors, distributed over huge areas in the solar field, which will inevitably drive down the performance of these plants. Accurate monitoring of degradation (Sutter et al., 2012) and soiling of CSP candidate materials with proper devices as demonstrated in Sutter et al. (2013) and Sansom et al. (2017) is crucial to evaluate their reflectance.

The application of anti-soiling coatings are among preventive solutions for keeping the dust away from the solar reflectors (Sarver et al., 2013). But for this technology to be effective, the performance of the mirrors should not be affected by the application of these films (Atkinson et al., 2015). To obtain a peak optical performance (Valenzuela et al., 2014), an extensive frequent cleaning must be

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Nomenclature

Acronyms

ACF	autocorrelation function
AIC	Akaike information criterion
BIC	Bayesian information criterion
CIEMAT	Centro de Investigaciones Energéticas, Medioambientales y Tecnológicas
CSP	concentrated solar power
D&S	Devices and Services Co
DLM	dynamic linear model
DNI	direct normal irradiance
JB	Jarque-Bera test
LB	Ljung-Box test
ML	maximum likelihood
MS	Markov switching
MSAR	Markov switching autoregressive
MSDR	Markov switching dynamic regression
NID	normal identically distributed
PSA	Plataforma Solar de Almería
PTC	parabolic-trough collectors
SE	standard errors
TRNSYS	TRaNsientSYstem Simulation

Greek symbols

β	coefficients dependent on the identified regime
ϵ_t	the residuals of the model
μ_{s_t}	regime dependent mean
ν	coefficients independent on the identified regime
ρ	coefficients of the lagged endogenous variable
σ	variance of the Gaussian distribution
θ	parameters of the model

Roman symbols

d	order of time series differencing
L	the likelihood
M	number of regimes
n	number of data points in the dataset
p	the order of the autoregressive term
$P-value$	the value obtained to accept or reject the statistical test
p_{ij}	the probability of going from a state i to a state j
q	order of moving average
s_t	a random variable
t	the time
X	the regressors
Y_t	the reflectance time series
Z	the regressors

applied, which is considered to be the most effective and widely used solution for handling the issue of dust deposition and adhesion to solar concentrating surfaces. For benign cleaning methods, such as non contact washing using pressurized water, innovative approaches have to be investigated (Anglani et al., 2017). In order to preserve the ability of reflectors to effectively focus the direct sunlight onto the solar receiver, an acceptable specular reflectance value in the wavelength range of the solar spectrum must be maintained. It is considered that an average reflectance above 90% measured at a 670 nm must be adopted in order to produce the planned energy output and, thus, preserve the economics of the plant (Cohen et al., 1999).

The soiling rate depends greatly on the prevailing weather conditions (Bergeron et al., 1981; Heimsath et al., 2010; Fernandez-Garcia, 2012; Burgaleta et al., 2012; Bouaddi et al., 2017). For example, the combined effect of light rain and wind severely pollutes the surface of the mirrors (King and Myers, 1980), while strong rainfalls effectively eliminate the adhering dirtiness. The adopted cleaning frequency may change seasonally as in Jones et al. (2007), where the reflectance obtained during winter with no artificial cleaning applied is almost equivalent to the reflectance obtained by applying frequent artificial cleaning during summer. Also, as concluded by Roth and Pettit (1980), the state of a mirror influences the dust accumulation rate. The authors pointed out a sharp drop of 0.0085 reflectance units/day for newly exposed mirrors, but as dust accumulation increases the soiling rate slows down. The possible reason for this might be that the probability for a particle to settle on a mirror surface is lower when the surface is covered with other dust particles than when the mirror is totally clean.

To obtain accurate energy production estimations under real outdoor conditions, Deffenbaugh et al. (1986) incorporated a soiling factor in the calculation of reflector's optical efficiency. For simulation purposes, reflectance is usually treated as a constant input, annual average, as in Blair et al. (2014) and Quaschning et al. (2001). When deciding on the best cleaning frequency to adopt in CSP plants, reflectance dynamics and various other variables (such as rainfall) should be taken into account. To determine a suitable cleaning frequency, Jones et al. (2007) proposed a formula where variables such as the constant annual soiling rate, the number of natural cleaning, and the effectiveness of the cleaning are considered. On the other hand, Bergeron (1982) used a simplified reflectance formula, which relies on the assumption that the reflectance evolves over time as a constant daily reflectance loss until reaching a plateau level. A different method was followed by Kattke and Vant-Hull (2012), suggesting a time-average reflectance based on film growth assumption. A time series approach was adopted in Bouaddi et al. (2015), where dynamic linear models (DLM) were applied to model the cumulative soiling of mirrors in Agadir (Morocco).

Unlike cumulative soiling, which is characterized by a continuous decreasing trend with some stochastic variation unless a strong natural cleaning event brings back the reflectance to high levels, regularly cleaned mirrors exhibit various swings (gains and losses of reflectance) and follow completely different dynamics dictated by the seasonal soiling, the frequency and efficacy of the artificial cleaning and the effectiveness of natural cleaning. By adopting a regular cleaning frequency (2, 6, and 12 days), Roth and Pettit (1980) showed that the reflectance oscillates around a long term average. However, this is not necessarily the case when the time between successive cleaning of reflectors is not equally spaced (Burgaleta et al., 2012), or when heavy soiling causes the overall average reflectance to severely drop during a dusty season. Since it could be advantageous to alternate between different cleaning methods (Jones et al., 2007) with each washing method having its own frequency of use, the resulting reflectance level may change over many cleaning cycles. In their work, Ba et al. (2017) proposed a modeling tool based on a finite horizon Markov decision process to decide on the optimal cleaning decision. However, the reflectance data used in their work does not build upon real site data.

This paper proposes a set of models based on Markov regime-switching (MS), which introduce the idea of changing regimes, to describe the reflectance dynamics of cleaned reflectors in CSP plants. This approach was applied on frequently cleaned CSP mirrors exposed for two years in Almería, Spain. This period of measurement is long enough to capture the seasonal aspects of reflectance change under the adopted washing frequency and the prevailing weather conditions. Key elements affecting the soiling, such as the rainfalls and the implemented cleaning frequency as well as the dustiness state of the mirror, are incorporated into the proposed models. To evaluate how this new modeling approach of reflectance works compared to simplistic approaches, it was tested against three other reflectance scenarios using the simulation results of a 30 MWe plant without storage in TRNSYS© software.

2. Methodology

In this section, the studied soiling data collected in PSA are presented. Also, explanations of the detailed modeling approach for building and comparing Markov regime-switching models and implementing reflectance assumptions in TRNSYS©simulation software are laid out.

2.1. Reflectance data

The data used in this study are the reflectance time series of second surface silvered-glass mirrors exposed outdoors for two years period at the PSA, in Almería (Spain). The PSA, which belongs to the Energy, Environment and Technology Research Center (CIEMAT), is the largest CSP research, development and test center in Europe and it is representative of locations where CSP plants are deployed. The exposure test benches were facing south and adopted a 45° inclination angle, which is appropriate since it is near the location latitude 37°, in addition to being used in many soiling studies (Morris, 1980; Bergeron et al., 1981).

Among the five types of reflectors deployed in this investigation, only reflectance data of the test bench's forth column is studied here (see Fig. 1). Reflectance measurements were performed on two mirror samples of dimensions 400 x 400 mm with 3 mm thickness. Since dust distribution on the mirrors is not uniform, a mask was used as medium to perform three measurements on the same spots of each mirror. Thus, the obtained reflectance is the average of the six reflectance measurements. The reflectance data were measured using the Devices & Services (D&S) 15R-USB portable specular reflectometer (Devices& Services, 2012), see Fig. 2. This equipment has a restricted wavelength range between 635 and 685 nm (with a peak at 660 nm), and suffers from incidence angle limitations Since the amount of reflected light on a surface depends on the incidence angle of the incoming rays (with this influence being more crucial for soiled mirrors),ideally it should be varied from near normal to 70° (Sutter et al., 2018) to adequately evaluate how varying incidence angles coupled with dust obstruction affect the amount of interceptedrays within the acceptance angle. However, current portable reflectometers are quite limited and do not possess this feature. This instrument remains widely used for measuring reflectance (Meyen et al., 2010). The configuration used to perform the reflectance consisted in using a 12.5 mrad acceptance angle with regular calibration of the instrument to ensure the correctness of the measurements.

Before applying the MS modeling technique, the reflectance data are normalized by dividing the measured reflectance by the reflectance of the clean new second surface silvered-glass mirror, thus obtaining the cleanliness. In what follows, this normalized reflectance is called simply reflectance. Since the rainfall data are valuable for understanding and analyzing the soiling behavior, this parameter was recorded daily during the outdoor exposure period. Concerning the cleaning of mirrors, high pressure demineralized water was applied, which is the cleaning method typically used in CSP plants (Cohen et al., 1999). Biweekly washing cycle was adopted to clean the exposed mirrors (right after measuring the reflectance), which is considered as reasonable choice in semi arid environments (Burgaleta et al., 2012).

Due to the requirement of using regularly spaced data points while dealing with time series, some time irregularities of the last few measurements are excluded from the used data. Therefore, the exploited reflectance dataset covers a total of 670 days, which is a long enough period to capture the dynamics of soiling in CSP plants. In our used sample, if a reflectance data point was not equally spaced from its most recent measurement, it is considered as missing and its value is imputed via simple linear interpolation. Other imputation methods such as (Honaker et al., 2011) could be useful if data of climatic conditions are available. Fig. 3 illustrates the normalized reflectance dynamics over time. The standard errors of mean reflectance are small when mirrors are relatively clean. For the case of imputed data these standard errors are not significant since the standard deviation from the mean reflectance is not accounted for in the modeling approach.

The applied artificial cleaning is indicated in dashed red lines, whereas the daily rainfalls are marked in blue. The amount of rain from the beginning of the experiment to the end of September are quite dispersed and light, whereas the second period (from October onwards) shows heavier rainfalls especially during October, November, March and April. The absence of rain and less frequent applied artificial cleaning result in low values of reflectance in the months of July and August. Other factors such as soil dryness during summer months and the amount of suspended aerosols in the air may be enhancing and accelerating dust accumulation on the surface of the mirrors. This also has to do with the fixed number of cleaning passes that are enough for restoring high reflectance during winter but are insufficient during summer. Conversely, the months with the combined effect of artificial cleaning and rainfall show high reflectance levels.

The soiling on the short term might appear merely as loss and recovery of reflectance. However, reflectance measured over many cleaning cycles (for a period of 670 days in our case) exhibit patterns that point out underlying dynamics that are a combination of site condition, cleaning intervention and seasonal variation. These changing dynamics call for switching parameters depending on the different site conditions. Our modeling approach based on MS tries to unveil these dynamics.

2.2. Approach

This section introduces the Markov regime-switching framework along with the description of key categories of MS models. Also, it describes the approach followed for suggesting and comparing MS models which capture the soiling dynamics, in addition to explaining the reflectance scenarios implemented in the TRNSYS©simulation software.

2.2.1. Markov regime-switching models description

A first attempt to model the data using non-switching models (i.e. a linear AR, ARX, or ARIMA (Sumway and Stoffer, 2006)) was performed. In order to apply these models, the stationarity of reflectance time series must be satisfied. Thus, differencing was performed until this requirement is obtained.

The best ARIMA(p,d,q), where p is the order of the autoregressive term, d is the order of differencing and q is the order of moving average, revealed that the best model has a differencing of order d = 2, as confirmed by performing the augmented dickey fuller test, and p = 3. By performing residual diagnostics, the autocorrelation test is

Fig. 1. The biweekly cleaned second surface silvered-glass mirrors exposed at the PSA (Spain).

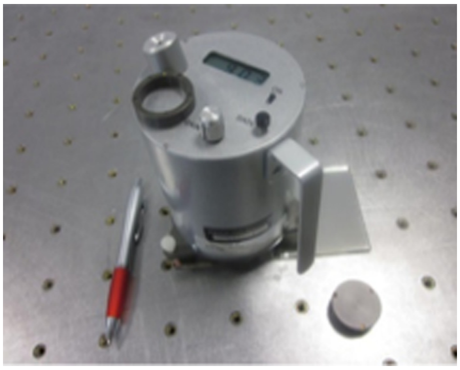


Fig. 2. The instrument used for reflectance measurements.

successfully passed, but the normality of residuals is violated. Moreover this model gives poor performance, log-likelihood equals 42. This poor result did not change with artificial cleaning or rain included as regressors.

In this paper, the proposed approach uses non-linear time series models that are state-dependent and are not constrained to only using constant parameters that just remain the same over many cleaning cycles.

MS methods are extensively used in econometric studies (Goldfeld and Quandt, 1973; Hamilton, 1989). These types of models are especially applied to describe the economic business cycles. The non linear time series approach introduced by MS are also used to model and analyze the data in diverse fields, such as wind forecasting (Shen and Ritter, 2016), hydrology (Akintug and Rasmussen, 2005) and psychology (Hamaker and Grasman, 2012). The strength of MS techniques stems from their ability to model the nonlinearity exhibited by time series using the concept of regime changing dynamics, meaning that the parameters of the model can change depending on the identified regimes.

In MS models, an unobservable random variable S_t follows a set of regimes M, where $S_t \in 1,...,M$. The transition probabilities describe the process of switching between M regimes following a first order Markov chain. The probability of going from a state i at time $t-1$ to a state j at time t is defined in Eq. (1):

$$P(S_t = j|S_{t-1} = i) = p_{ij}, \tag{1}$$

For the case of two switching regimes, for example, the matrix of transition probabilities can be expressed as follows:

$$P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix}, \tag{2}$$

where p_{11} is the probability of being in regime 1 and staying in that regime (this is also the case for p_{22} in regime 2), whereas p_{12} and p_{21} inform about the probabilities of going from a regime to another.

Within the framework of MS, there are many interesting models that could be used to model non linear time series. In this paper, we are primarily concerned with Markov switching autoregressive (MSAR) models of the class MSM(M)-AR(p) (Krolzig, 2013) and Markov switching dynamic regression models (MSDR)(Frühwirth-Schnatter, 2006).

MSM(M)-AR(p) refer to the class of models where the mean level is allowed to switch between regimes. The importance of these models arises from their ability to account for a changing mean, depending on the identified regime, which in the present case describes the targeted average reflectance of regularly cleaned mirrors in CSP plants. Since this targeted reflectance may change with varying cleaning strategies or unexpected weather conditions, it is allowed to change between regimes. Also, these models allow for incorporating autoregressive components of order p (order of lagged endogenous variables), which are able to capture the effect of past values of reflectance on current values, thus taking into consideration the effect of past dirtiness of the mirrors on their current reflectance. This model is expressed in Eq. (3) (Hamilton and Raj, 2013):

$$Y_t - \mu_{S_t} = \sum_{k=1}^{p} \rho_k (Y_{t-k} - \mu_{S_{t-k}}) + \epsilon_{S_t}, \qquad \epsilon_{S_t} \sim NID(0, \sigma_{S_t}^2), \tag{3}$$

where Y_t is the time series under study, the reflectance in our case, μ_{S_t} stands for the regime dependent mean, and ρ_k represents the autoregressive coefficient. p and M are, respectively, the order of the autoregressive term and the number of regimes. ϵ_{S_t}, known as the error conditional on the regime, is independent and identically distributed and follows a Gaussian distribution with mean 0 and variance σ.

Another interesting class of models used in this study are the MSDR. These models allow, in addition to the switching mean and autogressive components as in MSAR, to include exogeneous variables which are suspected to affect the dynamics of observed time series. Their mathematical formula is given by Eqs. (4) and (5):

$$Y_t = \mu_{S_t} + \sigma_{S_t} \epsilon_{S_t} \tag{4}$$

where μ_{S_t}, the conditional mean of Y_t, is formulated as follows:

$$\mu_{S_t} = \beta_{S_t} X_t + \nu Z_t + \sum_{k=1}^{p} \rho_{kS_t} Y_{t-k} \tag{5}$$

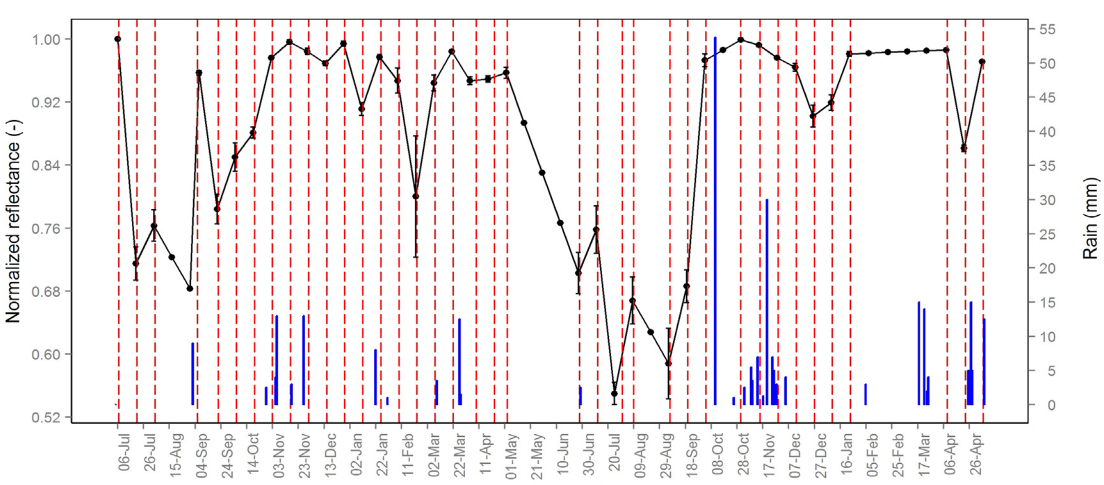


Fig. 3. The normalized reflectance evolution during 670 days.

In this expression, X_t and Z_t are the regressors. The β_{S_t} and ν denote, respectively, the regime dependent and regime invariant coefficients.

Computing the model parameters estimates (including the coefficients and the transition probabilities) are performed using the maximum likelihood (*ML*) estimation method. The two important processes required to describe the dynamics of MS models are the filtering and the smoothing process. The first consists in obtaining regimes probabilities by updating based on the recent information, whereas the second enables the exploitation of the entire information contained in the data to obtain the smoothed regime probabilities. The *ML* algorithms for computing the filtering and smoothing of the transition probabilities are developed and extensively explained in Hamilton (1989) and Kim (1994).

2.2.2. Building MS models

MS modeling requires first deciding on the number of the switching regimes. By visually inspecting the reflectance data (see Fig. 3), it is considered that the reflectance evolves between two regimes. One regime with an upper average reflectance, which occurs when the soiling rate is low or/and the cleaning (natural and/or artificial) is frequent, versus another regime characterized by a lower average reflectance due to high soiling rate or/and irregular and infrequent cleaning. If higher frequency measurements were available, it would be possible to capture three or more regimes, but in our case the data at hand suggested two regimes. The second assumption to be made is about the nature of the transition probabilities between regimes. Here, it is considered that the probabilities of going from one regime to another are constant over time.

In order to propose appropriate MS models, the following reasoning is considered. First, the reflectance of frequently cleaned reflectors tends to fluctuate around a mean value which depends on many soiling factors. Thus, regime-dependent mean models are selected.

Second, based on the assumption that the state of the reflectors (the level of their dirtiness) is very important for modeling reflectance (as it was mentioned in Section 1), the inclusion of autoregressive terms is performed, meaning that the current state of the reflectance is dependent on *p* previous reflectance. This consideration enhances the MS models capability by allowing them to be dynamic.

Third, since rainfall and artificial cleaning impact the soiling at different degrees, both switching and non-switching regressors are used in the analysis. Here, artificial cleaning was treated as an explanatory variable taking a 0 or 1 value (0 when no cleaning is applied and 1 otherwise), whereas the amount of accumulated rainfall between successive measurements is used as the natural cleaning regressor.

2.2.3. Specifications of the MS models

A total of seven models are proposed to describe the reflectance data by incorporating parameters suspected to capture the soiling dynamics. In this study, a regime independent variance was adopted in all the proposed models, because using the alternative, that is a regime dependent variance, lead to poor performance (these results were not presented in the following analysis for brevity considerations). This means that the data does not endorse an error dependent variance which is correlated to the observed regime. The performance of these models will be compared in Section 3.

The first model, model 1, has a simple regime switching mean, MSM (2)-AR(0), which is expressed as:

$$Y_t = \mu_{S_t} + \epsilon_{S_t}, \qquad \epsilon_{S_t} \sim N[0,\sigma_{S_t}^2] \tag{6}$$

where Y_t is the reflectance time series and μ_{S_t} and σ_{S_t} are, respectively, the regime switching mean and variance. The parameters to be estimated for this model are $\theta = (\mu_1,\mu_2,\sigma,p_{11},p_{22})$.

In order to obtain more dynamic models, a lagged endogenous variable of order 1, also called autoregressive term, is accounted for. Lags of order 2 or more were also tested but resulted in poorer models as demonstrated by *AIC* and *BIC* criterion (again these models were not presented in the following analysis for brevity considerations). Meaning that the time dependency does not persist beyond 1 lag and that the most important predictor of reflectance is the most recent past reflectance (lag 1).

Models 2 and 3 belong to MSM(2)-AR(1) models. Model 2 is expressed as follows:

$$Y_t = \mu_{S_t} + \rho_{S_t} Y_{t-1} + \epsilon_{S_t}, \qquad \epsilon_{S_t} \sim N[0,\sigma_{S_t}^2] \tag{7}$$

where ρ_{S_t} is the switching coefficient of the one lag autoregressive term.

Model 3, on the other hand, uses a non-switching coefficient $\rho_{S_t} = \rho_1 = \rho_2$.

To extend this analysis, models 4, 5, 6 and 7 belonging to MSDR class of models are studied. They are expressed as:

$$Y_t = \mu_{S_t} + \rho_{S_t} Y_{t-1} + \beta_{S_t} X_t + \epsilon_{S_t}, \qquad \epsilon_{S_t} \sim N[0,\sigma_{S_t}^2] \tag{8}$$

where β_{S_t} denotes the regime dependent coefficient of the regressor X_t. In the case of a non-switching regressor, the coefficients remain the same across regimes, that is $\beta_{S_t} = \beta_1 = \beta_2$.

In models 4 and 5, the rainfall is introduced as an explanatory variable. In model 4, both the rainfall regression and the one lag autoregressive coefficients are allowed to vary depending on the regime, while they both remain constant in model 5.

Two additional models (6 and 7) are considered. They both include the rain and artificial cleaning as explanatory variables in addition to a switching mean and autoregressive lag of order one. Both cases of switching (model 6) and non switching coefficients (model 7) are investigated. Table 1 summarizes all models suggested to capture the

Table 1
Summary of the suggested MS models.

Models	Category	Parameters					
		Switching mean	Switching autoregressive lag	Non switching autoregressive lag	Switching explanatory variable	Non Switching explanatory variable	Non switching variance
Model 1	MS(2)-AR(0)	+	−	−	−	−	+
Model 2	MS(2)-AR(1)	+	+	−	−	−	+
Model 3	MS(2)-AR(1)	+	−	+	−	−	+
Model 4	MSDR with rainfall as explanatory variable	+	+	−	+	−	+
Model 5	MSDR with rainfall as explanatory variable	+	−	+	−	+	+
Model 6	MSDR with both rainfall and cleaning as explanatory variable	+	+	−	+	−	+
Model 7	MSDR with both rainfall and cleaning as explanatory variable	+	−	+	−	+	+

soiling dynamics.

2.2.4. Evaluation of the MS models

In order to compare the performance of the proposed models, the log-likelihood, the Akaike information criterion (*AIC*), and the Bayesian information criterion (*BIC*) are computed. *AIC* is best suited to compare models with different number of parameters, thus favoring parsimonious models (Akaike, 1998). *BIC*, also called also Schwartz criteria, is equally used for comparing models but it is expressed differently (Schwarz, 1978). They are formulated in Eqs. (9) and (10):

$$AIC = \frac{-2log(L) + 2k}{n}, \tag{9}$$

$$BIC = \frac{-2log(L) + klog(n)}{n}, \tag{10}$$

where L is the likelihood, k is the number of parameters of the model and n is the number of data points of the studied dataset.

For the models to be adequate, their residuals must respect the hypothesis of normality and independence. In order to check the normality assumption, the Jarque-Bera (*JB*) normality test (Jarque and Bera, 1980) is performed. The autocorrelation function (*ACF*) and the Ljung-Box (*LB*) test (Ljung and Box, 1978) are used to check the independence of the residuals.

2.3. Simulation of different reflectance assumptions

Based on the energy output of a simulated CSP plant, the performance of the best selected model against other reflectance assumptions was evaluated. This simulation was performed in TRNSYS© (TRaNsientSYstem Simulation) program (Klein, 1988). A 30 MWe parabolic-trough collectors (PTC) plant without thermal storage, which is extensively studied in the literature as in Lippke (1995) and Patnode (2006), was used to perform the analysis. In this study, the number of mirrors was set to 182,000 m^2 solar field aperture area. The only adjustment made compared to (Patnode, 2006) consisted in using the Meteonorm software (Remund, 2014) to generate the meteorological data of Almería (Spain), where the reflectance data used in this study was measured.

Although numerous reflectance scenarios can be used as inputs to the simulation, this study is focused to four scenarios. Concerning the first and second scenarios, the reflectance is fed to the PTC component from the STEC library (Schwarzbözl et al., 2002) as a time series input using a data file. The actual reflectance data are the input to the first scenario (Variable-actual), whereas the second scenario uses variable reflectance of model 3 fitted values (Variable-fitted). A constant reflectance is used in the third and fourth scenarios, either as a maximum reflectance value of 0.96 in scenario 3, as suggested by Cohen et al. (1999), or as yearly average in scenario 4. The average reflectance for scenario 4 was taken from the average reflectance registered in a complete year from the measured reflectance data used in this work (in this case the year 2012), which is equal to 0.86. Since TRNSYS©performs hourly simulation, 1 h time step, the biweekly measured reflectance is interpolated by keeping it constant for 336 h (that is the two weeks period between two measurements). The comparison of the different scenarios is performed by simulating the energy (MWh) generated in each of the identified regimes during a year.

3. Results

This section includes parameters estimation and comparison of MS models where the best models are selected based on model selection criteria already established. Then, the models adequacy is judged by checking the normality and independence of their residuals. Finally, the smoothed and the filtered regimes are displayed and analyzed, and the simulation results computed by TRNSYS© are presented.

3.1. Model estimation

Using the likelihood estimation method, the parameters and their corresponding standard errors (SE) are computed. Table 2 shows the different parameters estimated for each model (see Table 1) and their corresponding SE. The switching parameters are reported for each of the models. When there is no switching parameter the values of a single regime are presented. Here, β^{rain} and β^{cl} refer to the rainfall and artificial cleaning coefficients, respectively. Since the variance of the residuals leads to poorer models (see Section 2.2.3), a constant residual variance applies to all models.

As can be observed in Table 2, the mean of all the proposed models switches between a high and a low average reflectance, either belonging to a “clean”or a “soiled” regime. The low mean, the soiled regime mean, of models 1–5 ranges between 0.68 and 0.69, whereas it ranges between 0.93 and 0.95 for the clean regime. Models 6 and 7 present a relatively higher soiling mean ranging between 0.70 and 0.71 in the soiled regime versus a mean between 0.94 and 0.95 in the clean regime.

The * and ** refer to 5% and 10% significance level, respectively. The significance of the coefficients (Davison, 2003) is evaluated to assess their relevance in the MS models. Dividing the coefficients by their corresponding SE informs about the *z−statistic* and consequently the *P−value*. For example when $p < 0.05$ the corresponding parameter is significant at a 5% significance level. As can be concluded from Table 2, the switching mean is significant for all the models and across all regimes, while the autoregressive coefficient ρ_{S_t} is solely significant in model 2 first regime while being insignificant in the other models.

Table 2
Parameters estimates of the suggested MS models.

Models	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
Parameters	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
μ_1	0.947*	0.011	0.943*	0.016	0.944*	0.013	0.939*	0.014	0.935*	0.013	0.945*	0.037	0.949*	0.029
μ_2	0.691*	0.019	0.685*	0.020	0.688*	0.022	0.691*	0.020	0.688*	0.021	0.716*	0.039	0.700*	0.031
ρ_1	–	–	0.355**	0.210	0.171	0.128	0.068	0.322	0.127	0.133	0.040	0.173	0.116	0.133
ρ_2	–	–	0.057	0.162			0.010	0.178			0.006	0.378		
β_1^{cl}	–	–	–	–	–	–	–	–	–	–	−0.033	0.045	-0.015	0.029
β_2^{cl}	–	–	–	–	–	–	–	–	–	–	−0.006	0.038		
β_1^{rain}	–	–	–	–	–	–	0.001	0.001	0.001	0.001	0.028*	0.008	0.001	0.001
β_2^{rain}	–	–	–	–	–	–	0.027*	0.008			0.001	0.001		
$\log(\sigma)$	2.830*	0.110	2.855*	0.112	2.840*	0.111	−2.880*	0.118	−2.865*	0.112	−2.886*	0.121	−2.868*	0.113

* 5% significance level.
** 10% significance level.

Concerning the rain coefficient, it is significant in model 4 s regime, where it appears to have a positive effect on the soiled reflectors while not impacting the clean regime. This is also the case for the soiled regime of model 6. These results are reasonable since the rain effect is greater with more accumulated dirt on the surface of the reflectors. On the other hand, the artificial cleaning regressor does not seem to be significant neither in the switching case (models 6) nor in the non-switching case (model 7).

3.2. MS model selection

This section presents the results of applying the evaluation parameters to the MS models (see Section 2.2.4) to assess their performance. Table 3 includes the results of this evaluation.

According to *AIC*, model 5 is best suited for modeling the soiling dynamics because it presents the highest value, followed by model 3. However, *BIC* favors model 3 followed by model 1. The log-likelihood attributes the best value to model 6, but for parsimony considerations, *AIC* and *BIC* are considered to be the best ways to judge the suitability of a model. Model 6 shows the worse AIC, whereas models 6 and 4 show the worst *BIC*. Based on these results, model 5 and 3 show the best performance compared to the other models.

By examining the matrix of transitions (see Eq. (2)), model 5 indicates that the probability of being and remaining in a regime is very high $p_{11} = 0.88$ and $p_{22} = 0.95$, while the probability for switching from a regime to another is very low, $p_{12} = 0.12$ and $p_{21} = 0.05$. The matrix of transitions in the model 3 shares almost the same probability values.

3.3. Residuals diagnostics

In this section, residuals diagnostics are performed as explained in Section 2.2.4. By applying the JB test on the standardized residuals of the model 5, a $P{-}value$ of 0.57 is obtained, meaning that the normality assumption is not rejected, as this value is greater than significance levels. Moreover, this model indicates the independence of its residuals by succeeding the LB test and with all their lags being inside the 95% significance level as can be seen in Fig. 4 (a). Passing both of these tests suggests the adequacy of this model. Model 3, as well, succeeded both the normality and independence tests. As can be observed in Fig. 4 (b), the visual inspection of the ACF reveals the independence of the standardized residuals. The *JB* test resulted in a $P{-}value$ of 0.18, greater than 0.05, signifying that the hypothesis of normal residuals cannot be rejected at a 5% significance level.

To conclude, according to this analysis and for parsimony consideration the use of rain regressor in the model 5 is not pertinent, thus making the model 3 sufficient for adequately modeling the reflectance data. Therefore, the model 3 (presented in Eq. (11)) is selected as the best one.

$$\begin{cases} Y_t = 0.944 + 0.171 y_{t-1} + \epsilon, & \text{Regime 1} \\ Y_t = 0.688 + 0.171 y_{t-1} + \epsilon, & \text{Regime 2} \end{cases} \tag{11}$$

With the error following a normal distribution with mean zero and $log(\sigma) = 2.840$.

3.4. The identified clean and soiled regimes

The identified periods of the model 3 are shown in Figs. 5 and 6, where probabilities greater than 0.5 illustrate the prevailing regime. Both the filtered and smoothed regimes probabilities are displayed in these figures. Since the smoothing process uses the complete data for probability estimation, it is used to identify the prevailing regimes. Fig. 5 displays the probabilities of the first regime, which was called the soiling regime. The displayed probabilities indicate that the soiling periods identified by the model 3 range from 03/08/2011 to 07/09/2011 and from 11/07/2012 to 03/10/2012. Clearly, these periods suffered from high soiling rate and infrequent cleaning. Fig. 6 displays the second regime, the clean regime, with a higher mean reflectance. According to the smoothed transition probabilities, these periods range from 21/09/2011 to 27/6/2012 and from 17/10/2012 to 06/05/2013.

Once the two regimes are identified, the selected model 3 fit was compared to the measured reflectance data and to the model 5 fit, which was identified as the second best one. Fig.7 shows that the fitted models adopt similar patterns as in the actual reflectance data. Both models 3 and 5 look similar, they almost fit equally good, except in few points. But the consideration taken to effectively choose the best model is parsimony. Meaning if two models fit the same, the model with the least number of parameters,in this case models 3, is the best. This winning model fit is less suited for unexpectedly low values, but in general terms the model remains a good fit to the measured reflectance.

3.5. Simulation results

The purpose for this simulation is to test the use of the best MS model in improving power prediction. Based on the regimes identified in Section 3.4, the comparison of the reflectance assumptions was conducted during the year 2012. The periods identified during this year are the two clean regimes ranging from 01/01/2012 to 10/07/2012 (clean 1) and from 17/10/2012 to 31/12/2012 (clean 2), in addition to the soiled regime ranging from 11/07/2012 to 16/10/2012 (soiled 1).

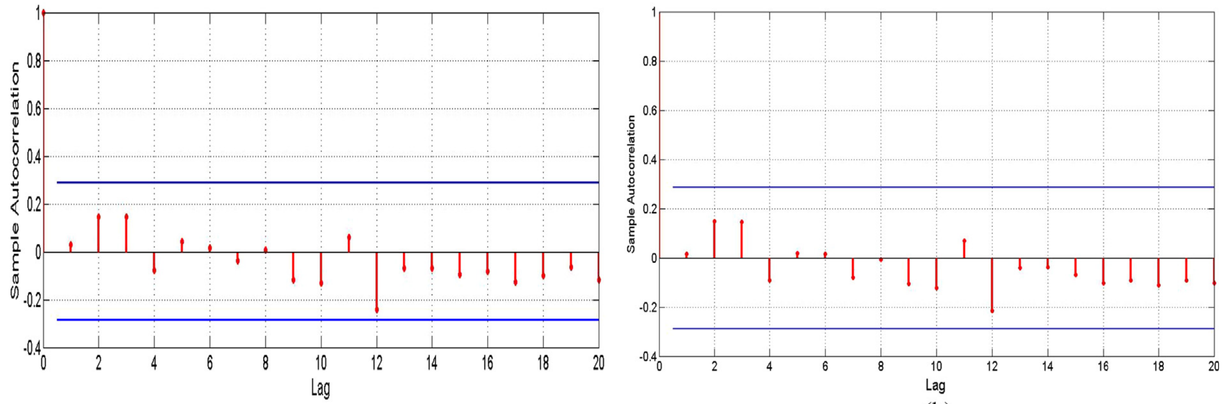
Table 4 presents the results of the simulations obtained by adopting the four reflectance scenarios described in Section 2.3. 11,127 MWh is the yearly accumulated output produced under the Almería site weather conditions and adopting the reflectance measured under real exposure conditions (that is, scenario 1). Fig. 8 illustrates the comparison of the different scenarios performed by dividing every regime output (MWh) by the output produced during the entire year using actual reflectance (scenario 1).

For a clearer understanding of the results, it deserves to mention that the outputs of these regimes are not mutually comparable since they cover different time duration. This is the reason, for example, of having much smaller bars in regime “clean 2” (which is quite short) than in regime “clean 1” (the longest one).

As can be seen in Table 4 and Fig. 8, using the maximum reflectance (scenario 4), obviously, delivers an overoptimistic output with respect to the measured reflectance (scenario 1). For example, in regime “clean 1” this value is even larger than the power produced during an entire year of actual reflectance (102%), which indicates that using a high reflectance level is erroneous when the necessary cleaning required to attain such high levels is not strictly respected. This scenario is only as good as the MS fitted model during regime “clean 2” because of its relatively short duration. By using the yearly average reflectance (scenario 3), an output largely superior than the actual reflectance during the period “soiled 1” is obtained. Conversely, the average reflectance underestimates the output during the clean regimes by 6.2% in the regime “clean 1” and 2.0% in the regime “clean 2”. The fitted model proposed in this work provides a quite higher production in “clean 1” but this only due to the long duration of this regime (versus other regimes), thus causing the inconvenience of the hourly simulation, where biweekly values were interpolated, to overestimate the output.

Table 3
The performance of the proposed models.

Models	Log (L)	AIC	BIC
Model 1	56.169	−2.089	−1.895
Model 2	58.280	−2.137	−1.864
Model 3	57.558	−2.148	−1.914
Model 4	60.020	−2.126	−1.775
Model 5	58.701	−2.154	−1.881
Model 6	60.352	−2.056	−1.628
Model 7	58.866	−2.119	−1.808



(a) (b)

Fig. 4. Residuals autocorrelation function (ACF) (a) model 5 and (b) model 3.

Concerning the other cases, the fitted model delivers significantly better results close to the actual data, especially during regime "soiled 1", where using a yearly average or a maximum reflectance are clearly inaccurate.

The obtained results confirmed the excellent results of scenario 2 versus simplistic reflectance assumptions. This performance is even greater during the soiling regime, where using an average or a maximum reflectance value clearly misses the mark, thus making this modeling approach very useful in dusty regions where soiling is persistent.

Even when CSP plants adopt a predefined cleaning schedule, weather data are unpredictable and thus will definitely influence the cleaning decision. This work proposes a valuable methodology that accounts for switching parameters (regressors and means) to adjust for the change of reflectance under variable cleaning frequency and fluctuating weather conditions.

4. Discussion

Even when CSP plants adopt a predefined cleaning schedule, weather data are unpredictable and thus will definitely influence the cleaning decision. This work proposes a valuable methodology that accounts for switching parameters (regressors and means) to adjust for the change of reflectance under variable cleaning frequency and fluctuating weather conditions. This modeling approach is highly adaptable to other CSP sites. For example, using different numbers of regimes could be plausible depending on the cleaning frequency (artificial), stochastic natural cleaning occurrence, soiling rate and climatic conditions. Also, it provides very good models to be used for realistic CSP yield simulations and cleaning optimization studies.

The prediction of future reflectance values could be achieved with larger data set. This is indicated in Hamilton and Raj (2013) and Krolzig (2013) detailing the methodology for MS forecasting. To select the best models, the performance criteria evaluate the adequacy of the number of regimes as well as the parameters incorporated into the suggested models.

5. Conclusions

This study introduced a new approach for modeling the soiling of frequently cleaned reflectors in arid and semi arid environments. In addition to a proper handling of the reflectance non linearity, the suggested MS approach is capable of integrating important variables such as the seasonal soiling and the washing cycle frequency in modeling the soiling behavior. The reflectance data of biweekly cleaned mirrors studied in this paper follow two regimes, a soiled and a clean regime. To account for the average reflectance of a period characterized by its washing cycle and soiling rate, a switching mean component is used in the seven proposed models. Based on model performance criteria, AIC and BIC, and the residuals diagnostics, the best model comprises of a regime switching mean and a non switching autoregressive lag of order one, in addition to a regime independent variance.

The best selected model fits satisfactorily the measured data and provides good simulation results compared to other reflectance assumptions. This is particularly clear during the identified soiled regime where unrealistic fixed reflectance considerations, which ignore the seasonal soiling dynamics and the cleaning of the typical solar reflectors in a CSP plant, result in incorrect yield.

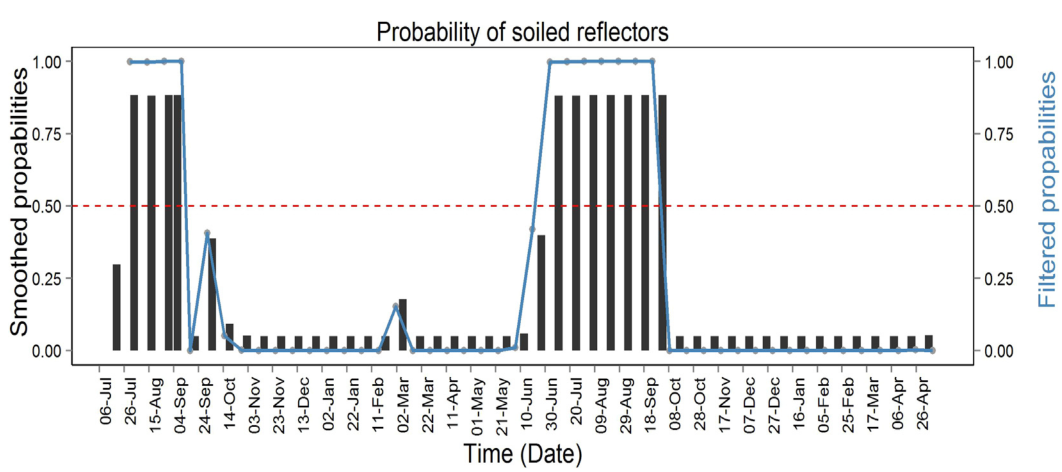


Fig. 5. The smoothed probabilities (black bars) and the filtered probabilities (blue line) of the soiling regime.

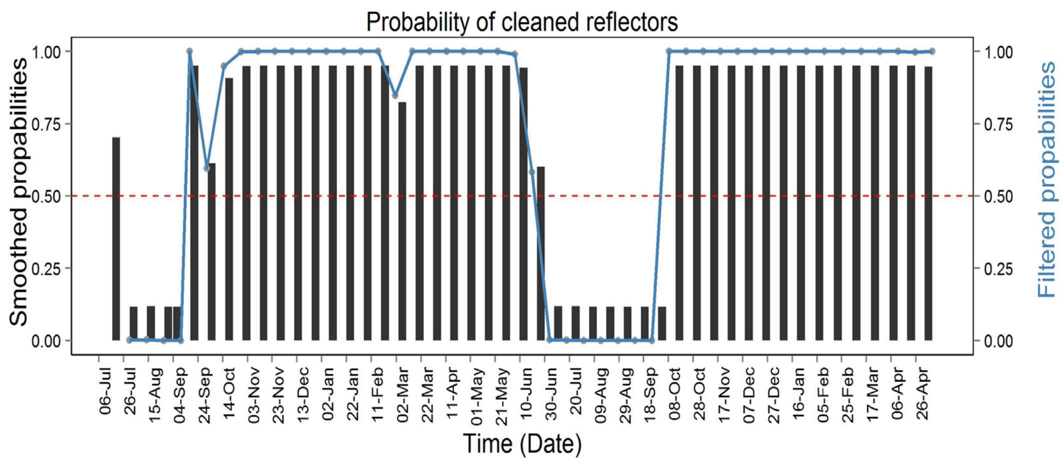


Fig. 6. The smoothed probabilities (black bars) and the filtered probabilities (blue line) of the clean regime. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

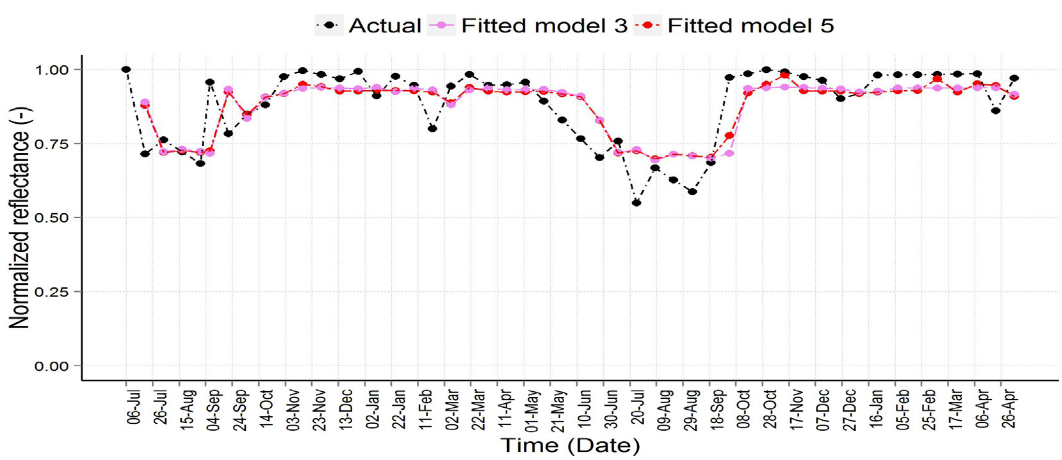


Fig. 7. The actual reflectance against the fitted models 3 and 5.

Table 4
The generated output (MWh) obtained by adopting the four reflectance scenarios.

Period	Date	Adopted scenario	Generated output (MWh)
All year	01/01/2012 to 31/12/2012	1: Variable-actual	11,127
Clean 1	01/01/2012 to 10/07/2012	1: Variable-actual	8429
		2: Variable-fitted	9738
		3: Average	7738
		4: Maximum	11,367
Soiled 1	11/07/2012 to 16/10/2012	1: Variable-actual	2308
		2: Variable-fitted	2626
		3: Average	5605
		4: Maximum	8215
Clean 2	17/10/ 2012 to 31/12/2012	1: Variable-actual	390
		2: Variable-fitted	287
		3: Average	168
		4: Maximum	329

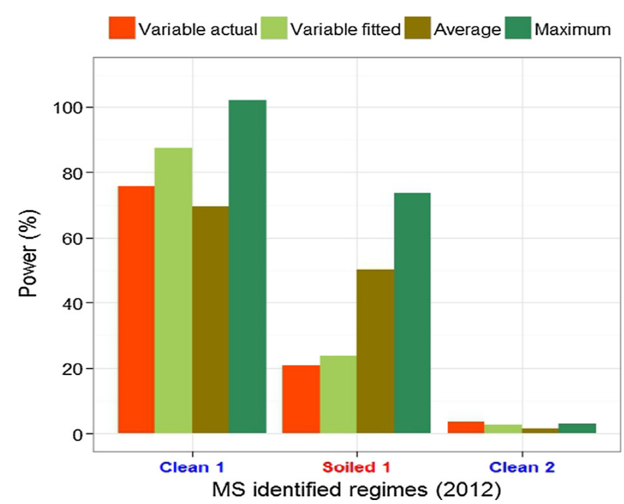


Fig. 8. Histogram of the simulation results of the four scenarios.

TRNSYS was used to compare the different assumptions on a hypothetical 30 MW plant. However, testing and validation of the developed approach on real production plant is highly valuable to gain general knowledge out of the simulations. Despite of the inconvenience of the hourly simulation causing the difference between the actual and fitted output, the selected model is believed to be the best approximation to the real reflectance dynamics. Very promising results have been obtained and a highly useful model was achieved, which is able to predict future reflectance values. Furthermore, the selected model could also be applied to more frequent reflectance data to improve its capabilities. Finally, the strength of the MS approach enables the use of as many regimes as it is considered adequate for describing the reflectance dataset at disposal, thus representing a promising option for greater accuracy in estimating the CSP yield in dusty environments.

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