

# Determining soiling losses on PV modules in a desert climate

**Soiling** | Understanding the impact of soiling on PV modules and thus the most appropriate cleaning regime, is critical to preventing losses in module power and plant yield. David Daßler, Stephanie Malik and Akshayaa Pandiyan of Fraunhofer CSP describe a statistical method they have developed for accurately characterising the losses from soiling in desert conditions

Irradiation losses due to external causes, such as soiling or shading, remain the prominent source of a PV module's energy yield cutback. Consequently, effort and investment to mitigate them becomes essential, especially in cases of maintaining a large-scale PV plant. This can be simplified by identifying and analysing the key parameters related to external losses and developing a method to estimate them based on the former.

Dust, dirt, sea salt and pollen, originating from air pollution caused by mining activities, construction, agricultural activities and other natural phenomena, can lead to accumulation of particulate matter on the surface of solar panels. This is termed as *soiling*. Soiling leads to current reductions in the PV module which further affects the power and energy yield, especially in dry or arid areas. In general, these losses are referred to as *soiling losses*.

Existing soiling can only be removed by cleaning events, which can either occur naturally (heavy rainfall) or manually (maintenance cleaning). Previous studies on soiling have focused on desert or dry regions, which are susceptible to large aerosols in air, but also occur consistently with large solar resources. A recent study [1] by Mejia et al. reported an efficiency loss of 7.4% for a PV panel operated for an average of 145 days during a dry period in California; this is an order of magnitude higher than the losses due to cell degradation. Similar case studies have supported the significant impact of soiling losses on energy yield for different regions, but efficient methods of quantitative prediction of soiling is still a challenging task

for researchers in PV modelling. The most important factor influencing the level of soiling losses are the dust properties (e.g. shape and size), moisture, humidity, frequency and intensity of precipitation, wind speed and the installation configuration of PV panels [2, 3]. A study by Haeberlin et al. [4], demonstrated the reversible effects of soiling losses before and after manual cleaning on a 60kW array. In addition, a recent work in Italy [5] reported a 6.9% reduction in performance for one site and 1.1% for another site not far from each other due to eight weeks of soiling. It can therefore be interpreted that large variability of soiling can occur even over short distances.

This article explains a method to determine soiling losses and to classify the soiling state of PV modules in desert climates, which can then be adapted for other climates based on PV plant system data.

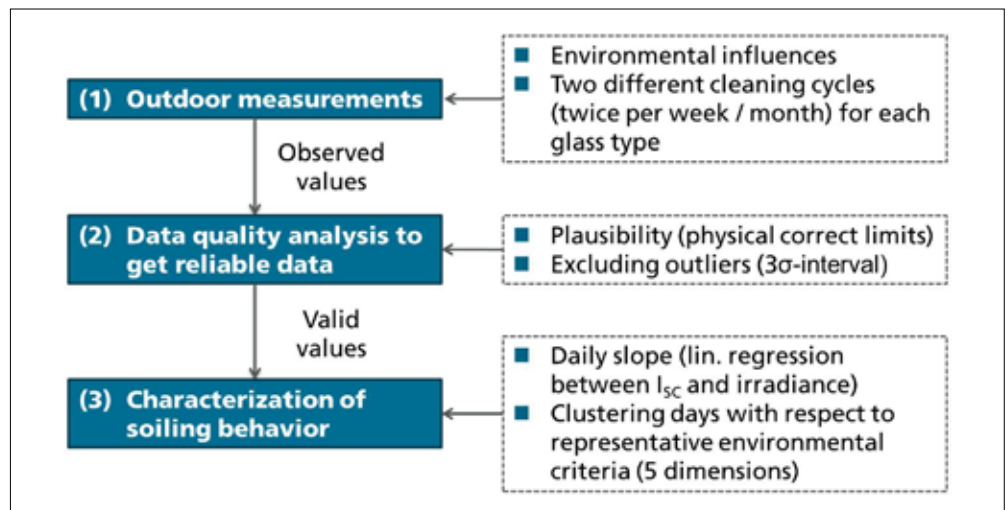
## Methods

The impact of soiling on a running PV system depends on the local conditions, as described before. In order to determine the meaningful local soiling behaviour and to be able to make statements about the cleaning intensity, an understanding of the relationship between environmental factors and PV performance is necessary. The following approach extends from outdoor measurements (performance data) to extensive data analysis. Figure 1 structures the approach of this article.

In the first part, PV modules were characterized at standard test conditions (STC: 1000 W/m<sup>2</sup>, 25°C, spectrum AM1.5) and tested under outdoor conditions with different cleaning cycles in a desert environment. This data contains detailed information about the state of natural soiling of the modules and relevant environmental influences over time.

The collected data was then filtered in

**Figure 1.** Flowchart of the investigations [8]

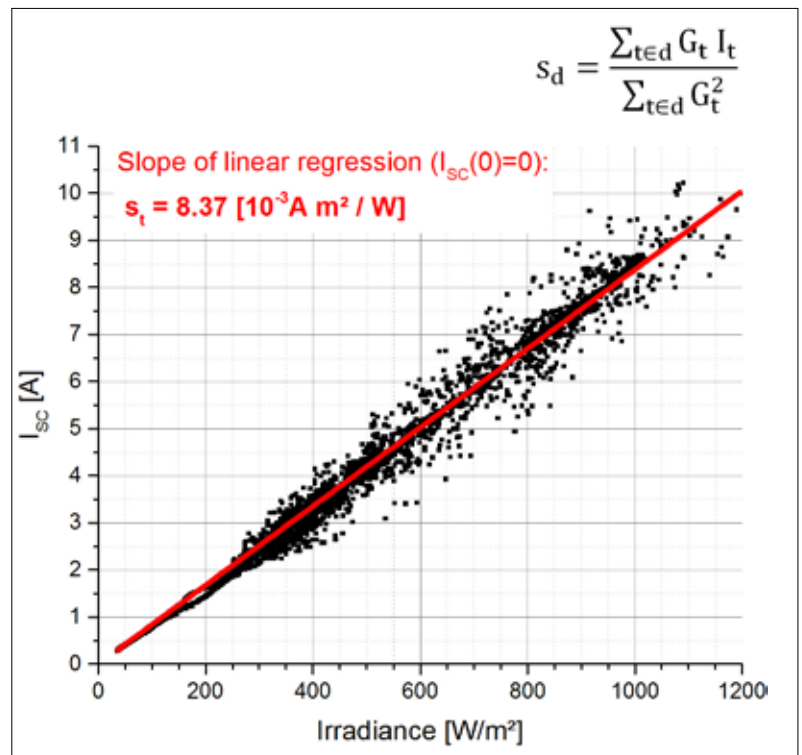


the second step in order to achieve valid information for further data evaluation. Finally, the soiling losses were determined based on filtered data, taking into account the mean ratio between irradiance and module short circuit current. The current is only slightly dependent on the temperature and is directly influenced by transmission losses due to dust deposition on the module glass. In addition, the days were clustered due to different influencing environmental conditions such that the soiling losses can be characterised by cluster information. These steps are described in detail further in this article.

**Outdoor measurements**

Several months of outdoor data was measured (see Picture 1) to receive data about the module performance and environmental conditions. The measurements were made at the outdoor research platforms of photovoltaic modules at "Green Energy Park" (GEP) in Ben Guerir, Morocco (near Marrakech), implemented in a partnership with Fraunhofer CSP. GEP is a solar testing, research and training platform, in the green town of Ben Guerir,

**Figure 2. Determination of daily mean ratio using slope of linear regression: E.g. relationship between  $I_{sc}$  and irradiance for one module on one day (09.06.2017) [8]**



developed by IRESEN with the support of the Ministry of Energy, Mines, Water and Environment and the OCP Group [6] to develop and provide the access to research

infrastructures and expertise at optimum costs. IRESEN (Research Institute for Solar Energy and New Energies) was established in 2011 in order to lead and promote



setting the standard in  
**PV soiling monitoring**  
 with  
**DustIQ**

[www.kippzonen.com/DustIQ](http://www.kippzonen.com/DustIQ)

Picture 1. Outdoor measuring set-up and installed PV modules in Green Energy Park of IRESEN, Ben Guerir, Morocco [8]



R&D in Morocco in the field of renewable energy.

For this investigation, four PV modules were measured individually. The PV modules were built at Fraunhofer CSP Module Technology Centre, Germany. Apart from the front glass, the modules have the same layout and the same materials (solar cells, encapsulation, backsheet). Two different types of front glass (ARC and non-ARC) were used to study the soiling behaviour due to the glass type. The modules' performance at STC lies close to each other: ARC modules (Mod\_1 and Mod\_2) show 245Wp, 37V and 8.9A and non-ARC modules (Mod\_3 and Mod\_4) 244Wp, 37.1V and 8.8A.

The module measurements (IV-curves and module temperature) were measured synchronously in a time interval of 10 seconds and between the measurements, every module is operated at maximum power point (MPP). The weather data, however, was measured every 60 seconds and dust particle concentration were measured with an interval of 10 minutes. Different cleaning approaches were applied for each glass type: twice per week and twice per month. This results in a "clean" and a "soiled" group containing both glass types.

**Data quality analysis**

The measured module data was synchro-

Soiling rate [%/day]		
Module	Mean	Max (abs.)
Mod_1	-0.27	-0.57
Mod_2	-0.23	-0.36
Mod_3	-0.31	-1.16
Mod_4	-0.22	-0.34

**Table 1. Maximum and average soiling rate [%/day] for each module.**

nised and filtered for further evaluation to avoid misinterpretations. The measured data have different intervals for various acquisition systems, therefore the weather data and the dust particle concentration were assumed as constant for the subsequent 60 s and 10 min interval, respectively. The data was processed for plausibility by imposing physical limits and statistical three-sigma limits [7]. This ensures that the quality of the analysing data used for characterising soiling losses is least affected by noise and outliers.

**Characterisation of soiling behaviour**

**Soiling losses**

To determine module or system soiling losses, the linear relationship between short circuit current ( $I_{sc}$ ) and irradiance ( $G$ ) was used (see Figure 2).

After linear regression in a specific time period, a representative average relation-

Parameter	Aggregation per day
Irradiance	Irradiance yield sum [kWh/m <sup>2</sup> ]
Dust particle (air)	PM total sum [10 <sup>3</sup> µg/m <sup>3</sup> ]
Relative humidity	RH mean [%]
Ambient temperature	T <sub>amb</sub> mean [°C]
Wind speed	WS mean [m/s]

**Table 2. Characteristic parameters for clustering.**

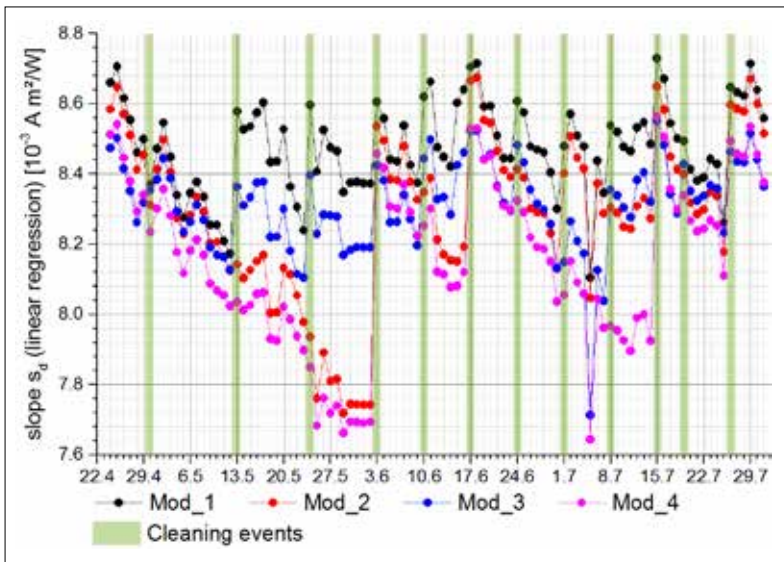
ship can be approximated. Due to the fact that the current is zero without any irradiation, it is assumed to use the linear regression model ( $I_{sc}$ ) intercepting at the origin:  $I_{sc} = s_d \cdot G$ .

The resulting slope of the regression coefficient ( $s_d$ ) characterises the quantitative conversion of irradiation energy into electrical current. In sense of this objective, the slope  $s_d$  determines the soiling state of the PV module.

The slope can be variably applied in terms of time period and PV module samples. In this case, the slope per day (sufficient data for a regression) and per module is determined to obtain a valid linear regression process. The slope  $s_d$  can be calculated as shown for any day (d):

Changes in the inclination of the regression slope from one day to another can be interpreted as changes in the soiling state





**Figure 3. Variation of daily slopes between  $I_{sc}$  and irradiance for four modules with different cleaning cycles [8].**

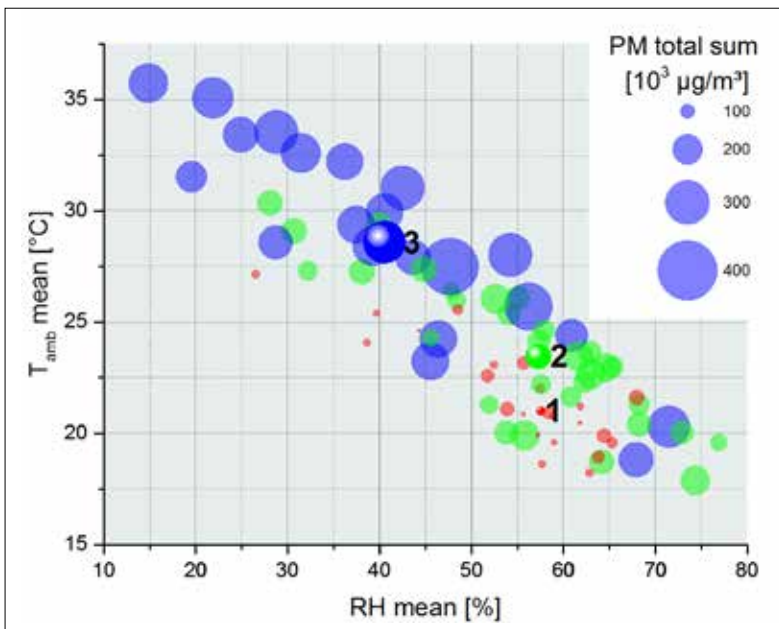
of the module (cleaning or soiling effect). This approach does not take in to account any degradation or malfunction of the PV module, the measuring equipment or the irradiance sensor (regular cleaning of the sensor was performed).

The daily slope differences ( $\Delta s_d$ ) were calculated between one day and the day before. If  $\Delta s_d$  is positive, a cleaning event has occurred (natural or manual); otherwise, the soiling effect has increased.

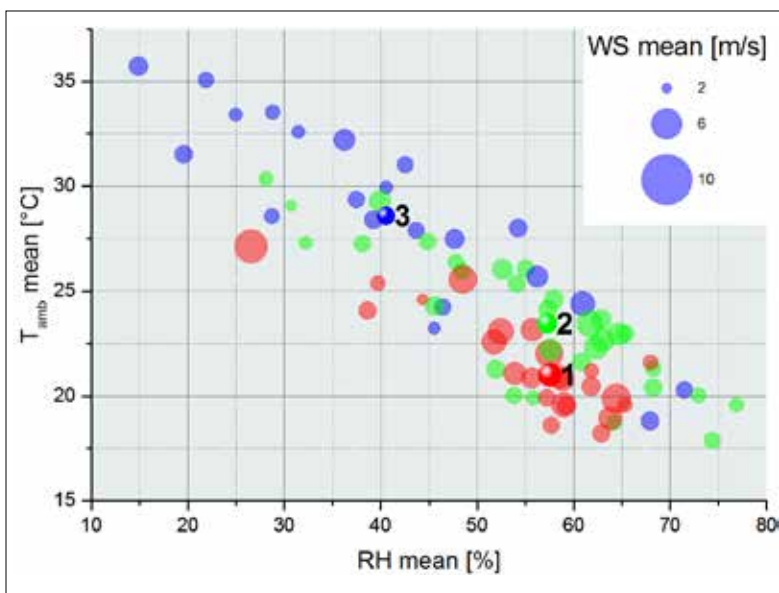
$$\Delta s_d = s_d - s_{d-1}$$

Using this approach the resulting slopes per day for each module in the given period are displayed in Figure 3. This includes manual cleaning events for comparison. The soiling behaviour per module can be considered as the decreasing slopes, and the various cleaning events can be deciphered from the abruptly increasing slope.

An average soiling rate can be calculated by linear regression of the decreasing slopes (normalised to the cleaned state of the module) until the next cleaning event. Table 1 shows the averaged soiling rate for the four modules. Due to changes in cleaning cycles and samples, this average soiling rate was determined individually per module, according to their soiling behaviour between two cleaning events. Nevertheless, Mod\_1 and Mod\_3 were cleaned more frequently than Mod\_2 and Mod\_4. Taking the results into account, Mod\_1 and Mod\_3 show a higher soiling rate than the more heavily soiled samples (see Table 1). The soiling rate of the cleaned modules is close to each other and this also applies to the group of soiled modules. On the contrary, a strong effect between both glass types can't be seen.



**▲▼ Figure 4. Results of five-dimensional clustering of environmental data into three clusters based on daily values (cluster 1: red; cluster 2 green; cluster 3: blue) [8]**



**Classification of environmental data**

In order to classify the environmental parameters with their day profile and their possible interaction with each other, the k-mean clustering method was used, which is generally known for cluster analysis in data mining. k-mean clustering means that  $N$  observations for  $n$  parameters are divided into  $k$  clusters, with each observation belonging to the nearest-distance (absolute difference) to the cluster centre (centroid). These cluster centres were determined iteratively by reassigning the observations to the next nearest center in each step. After which the mean for each cluster defines a new

cluster centre for the subsequent step.

The set of observations to be grouped is 75 days ( $N = 75$ ). A suitable cluster solution for this  $N$  with three or four clusters can be selected to avoid a very small cluster division of less than 10 days per cluster. This work shows the estimation of three clusters ( $k = 3$ ). The parameters used for clustering ( $n = 5$ ), aggregated per day (including night values) as sum or average, are listed in Table 2.

The quality of the standard k-mean method also depends on the randomly chosen initial cluster centres before the first iteration. To ensure a reliable minimum sum of distances within each cluster, a large number of repetitions (~10,000) of the k-mean cluster were realised.

The results of the five-dimensional clustering applied to the daily aggregated environmental parameters (listed in Table 2), are shown in Figure 4. Both graphs are based on the same data and clustering process, in which the colours represent the clusters. The difference between them is due to the chosen environmental parameters and their dependency on each other in their respective clusters.

From Figure 4 it can be seen that for this particular site:

- Cluster 1 is concentrated at high  $RH$  and moderate temperature.
- Cluster 3 is widely spread referring to  $RH$  and  $T_{amb}$ .
- The amount of cumulated air dust increases with increasing  $T_{amb}$  and decreasing  $RH$ .
- The influence of wind speed shows no clear tendency.

The ranges between the different clusters in terms of minimum, maximum and average values are listed in Table 3. Referring to these values, because of the multi-dimensional relationship, the clusters overlap for several parameters. The clearest distinction between the clusters is shown in the accumulated dust (PM total), whose values do not overlap.

Based on these results, each further day (past/future) can be assigned to one of the three clusters, if these five parameters are known for this day.

**Combination of soiling losses and clustered environmental data**

In the final step, the classified days can be combined with the determined  $\Delta s_d$  from one day to the other of each module. The manual cleaning events must be excluded in order to interpret the results based only

on environmental impact. These results are shown in Figure 5 and in Figure 6.

In each cluster the soiling effects ( $\Delta s_d < 0$ ) have the main emphasis, but natural cleaning effects ( $\Delta s_d > 0$ ) also occur. A different soiling behaviour with respect to the cluster can be seen. Cluster 2 shows the highest level of soiling followed by cluster 3 and 1. Different soiling behaviour between the cleaned and soiled modules, as well in comparison to different types of glass can be seen in Figure 6. This figure shows the mean  $\Delta s_d$  per module, per cluster, with its corresponding uncertainty ( $U(\Delta s_d)$ , error bars), to interpret the significance of the results. The relative mean of  $U(\Delta s_d)$  is approximately 5.4% with respect to all modules and clusters. The soiling behaviour of the more frequently cleaned Mod\_1 and Mod\_3 (ARC and non-ARC) in each cluster is worse than their corresponding soiled sample. This underlines the results of Table 1. When comparing the types of glass, the results are not as clear in the three clusters (Figure 6). In cluster 1, the non-ARC Mod\_3 and Mod\_4 show an advantage in contrary to cluster 2 and 3.

Which deviation in short circuit current corresponds to the determined  $\Delta s_d$ ? Table 4 tries to answer that, by assuming different irradiance levels.

**Final explanations**

It is not trivial to decipher the effects of soiling based on the type of glass chosen, cleaning cycles and weather parameters. The proposed approach tries to relate them to each other. The results shown are examples of possible relationships and represent the measured site in Morocco. Other locations worldwide may have different results. The explanations before showed how the results can be handled.

The results show a different soiling behaviour between the cleaned and dirty modules and a comparison of both types of glass in the different clusters of environmental conditions per day. It is also important to note that the mean values of slope differences of each module are found by all clusters in the first quadrant 'Soiling effect', which implies the decreasing slopes for all modules. The manual cleaning events are excluded in order to interpret the results only because of environmental impacts;

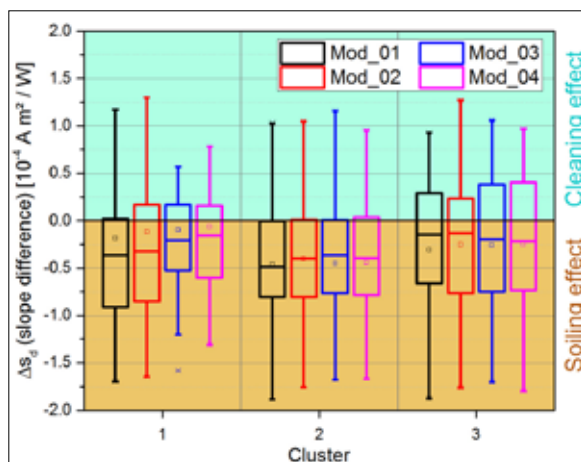
**Figure 6. Mean of slope difference  $\Delta s_d$  between two consecutive days per module and cluster [8].**

Parameter	Cluster 1	Cluster 2	Cluster 3
Irradiance [kWh/m <sup>2</sup> ]	5.5 – 8 (Ø 7.1)	1 – 7.8 (Ø 6.6)	4 – 7.4 (Ø 6.6)
PM total [10 <sup>3</sup> µg/m <sup>3</sup> ]	10.7 – 100.7 (Ø 59.1)	108.6 – 198.7 (Ø 155.5)	206.8 – 381 (Ø 262.7)
RH [%]	26.5 – 68 (Ø 55.1)	28.1 – 76.9 (Ø 55.5)	14.9 – 71.4 (Ø 40.9)
T <sub>amb</sub> [°C]	18.2 – 27.1 (Ø 21.6)	17.9 – 30.4 (Ø 23.7)	18.8 – 35.7 (Ø 28.6)
WS [m/s]	2.2 – 6.5 (Ø 4.1)	2.2 – 5.2 (Ø 3.5)	2.5 – 4.8 (Ø 3.4)

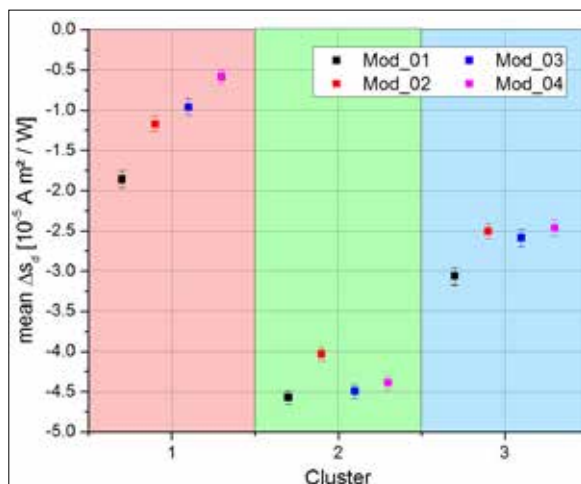
**Table 3. Characterisation of clusters: minimum, maximum and mean values for each parameter and cluster**

Irradiance [W/m <sup>2</sup> ]	Deviation in short circuit current [mA]		
	Cluster 1	Cluster 2	Cluster 3
1000	-11.3	-43.7	-26.5
800	-9.0	-35.0	-21.2
500	-5.6	-21.9	-13.3
250	-2.8	-10.9	-6.6

**Table 4. Deviation in  $I_{sc}$  determined per cluster by using mean value of slope differences (one day to the other) at different irradiances**



**Figure 5. Slope difference  $\Delta s_d$  between two consecutive days; box plots (extreme values, quartile (25, 50, 75%) and mean) for each module and each cluster [8]**



this could have resulted in higher slope differences. The soiling behaviour of the more frequently cleaned Mod\_1 and Mod\_3 is worse for both modules types in every cluster than their corresponding soiled sample, which underlines a hypothesis that a cleaned module surface is particularly more susceptible to soiling effects than an already soiled layer of particulate matter to attract more dust and dirt until a saturated soiled state is reached.

Another interesting point to highlight is the higher slope differences (day-to-day) of cluster 2 than those of cluster 3, despite the higher concentration of dust in cluster 3. Although cluster 2 has a lower dust concentration than cluster 3, the mean humidity in cluster 2 is higher (Table 3). On the other hand, it is assumed that increasing the density of the aerosol particles suspended in the atmosphere results in more sedimentation of dust particles on the module surface. This is an illustration of the complicated relationship between the various environmental parameters that influence soiling and the importance of the proposed method by clustering various environmental parameters and examining their soiling effects towards energy loss. Afterwards, the most important influencing parameters can be determined more precisely and then used to model the soiling effects on PV modules.

However, the end estimation of soiling losses is derived as a function of environmental parameters. Therefore, this work has the additional advantage that it can be used anywhere, if the environmental conditions are known. In a precision-based comparison, this method is very accurate in distinguishing between the module properties and the state of soiling of the modules. ■

#### Authors

David Daßler received his MSc in applied mathematics from Leipzig University of Applied Sciences. Since 2012, he has worked in Fraunhofer CSP's "Reliability of Solar Modules and Systems" group, specialising in yield analysis. In 2015 he began his PhD about yield modelling in desert climates.



Stephanie Malik has worked as an engineer in the "Reliability of Solar Modules and Systems" group at Fraunhofer CSP since 2012, focusing on outdoor measurements and yield analysis. Before joining Fraunhofer, she was active in the R&D department of Q-Cells, now Hanwha Q CELLS, for five years.



Akshayaa Pandiyan is currently working as a research assistant at Fraunhofer CSP, after obtaining her MSc in renewable energy engineering from the University of Freiburg. She shares an interest for research in renewable energy, computational programming and system modelling.



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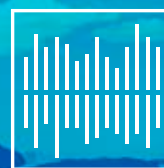
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