



# On the temporal modelling of solar photovoltaic soiling: Energy and economic impacts in seven cities



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## HIGHLIGHTS

- The energy and economic impacts of solar photovoltaic soiling were modelled.
- Relative net-present value change was defined to assess optimal cleaning intervals.
- We compared the soiling-induced efficiency and economic losses in seven cities.
- The efficiency loss is the lowest ( $< 0.04$ ) for Tokyo and highest ( $> 0.8$ ) for Doha.
- The optimal intervals are 23–70 days (manual) and 17–49 days (machine).

## ARTICLE INFO

### Keywords:

Solar PV  
Soiling  
Energy loss  
Economics  
Cleaning  
Renewable energy

## ABSTRACT

This work developed a framework to predict the energy and economic impacts of solar photovoltaic soiling. This framework includes the effects of relative humidity, precipitation and tilt angle on solar photovoltaic soiling. A concept of relative net-present value change was introduced to determine the optimal cleaning interval. The uncertainties in the economic analysis were accounted for using a Monte Carlo simulation method. The framework was used to study the soiling-induced efficiency and economic losses of solar photovoltaic modules in seven cities (*i.e.* Taichung, Tokyo, Hami, Malibu, Sanlucar la Mayor, Doha, and Walkaway). Overall, the efficiency loss (in ascending order) for Tokyo/Walkaway  $<$  Taichung  $<$  Sanlucar la Mayor  $<$  Malibu/Hami  $<$  Doha for a one-year study period. Doha experiences an efficiency loss over 80% for a 140-day exposure, while Tokyo has an efficiency loss less than 4% for a one-year exposure. Malibu has longest optimal cleaning intervals (70 days for manual cleaning and 49 days for machine-assisted cleaning) that leads to the relative net-present value changes of 1.7% and 1.1%. Doha has the shortest optimal cleaning intervals (23 days for manual cleaning and 17 days for machine-assisted cleaning) that leads to the relative net-present value changes of 21% and 19%. The work serves as an effective tool for designing optimal cleaning protocols for solar photovoltaic systems.

## 1. Introduction

World energy consumption was projected to increase by 28% between 2015 and 2040 in accordance with the rapid growth in electricity demand and economy [1]. Limited reserves of fossil fuels and widespread concerns over greenhouse gas (GHG) emissions from fossil fuel consumption stimulate extensive research in renewable energy development. As a major form of renewable energy, solar photovoltaic (PV) electricity generation has drawn an ever-increasing attention due to its abundance, accessibility, and technical maturity [2].

However, solar PV systems are plagued by the issue of natural

soiling whereby particulate matters (PM) accumulate on the surface of solar PV panels, resulting in light transmission blockage and irradiance reduction. The solar conversion efficiency of solar PV modules could be lowered by 4–25% due to the soiling [3–5]. Piliouguine et al. [6] found that an average daily energy loss of 2.5% was resulted by soiling. Solar PV soiling is especially a concern for the regions where there are frequent sandstorms or haze episodes [7]. This issue could also be exacerbated during dry seasons when there is insufficient rainfall to clean PV surfaces [8]. The soiling-induced efficiency reduction not only adversely affects the stability and overall energy performance of solar PV systems but also incurs additional economic and logistics requirements

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## Nomenclature

$C_D$	drag coefficient
$C_{DS}$	surface drag coefficient
$C_c$	Cunningham correction factor
$C$ ( $\mu\text{g}\cdot\text{m}^{-3}$ )	atmospheric aerosol concentration
$C_1, C_2, C_3, C_4$	empirical constants
$d_p$ (m)	particle diameter
$D$ ( $\text{m}^2\text{s}^{-1}$ )	Brownian diffusion coefficient
$g$ ( $\text{m}\cdot\text{s}^{-2}$ )	gravitational acceleration
$h$ (m)	reference height
$k$ ( $\text{JK}^{-1}$ )	Boltzmann constant
$LT$	life time of facilities
NPV (USD)	net-present value
$\Delta\text{NPV}\%$	relative NPV change
$R_{at}$ ( $\text{s}\cdot\text{cm}^{-1}$ )	atmospheric turbulence resistance term
$R_b$ ( $\text{s}\cdot\text{cm}^{-1}$ )	quasi-laminar resistance term
$Re_p$	particle Reynolds number
$r_d$ (m)	dry particle radius

$r_w$ (m)	wet particle radius
$r$	discount rate
$Sc$	Schmidt number
$St$	Stokes number
$T$ (K)	air temperature
$U$ ( $\text{m}\cdot\text{s}^{-1}$ )	mean wind velocity
$u_*$ ( $\text{m}\cdot\text{s}^{-1}$ )	friction velocity
$V_s$ ( $\text{m}\cdot\text{s}^{-1}$ )	sedimentation velocity
$V_d$ ( $\text{m}\cdot\text{s}^{-1}$ )	total deposition velocity
$z_0$ (m)	roughness length
$\rho_f$ ( $\text{kg}\cdot\text{m}^{-3}$ )	density of fluid
$\rho_p$ ( $\text{kg}\cdot\text{m}^{-3}$ )	density of aerosol particle
$\rho_D$ ( $\text{g}\cdot\text{m}^{-2}$ )	dust deposition density
$\mu$ ( $\text{kg}\cdot\text{m}^{-1}\text{s}^{-1}$ )	viscosity of air
$k$	von Karman constant
$\nu$ ( $\text{m}^2\text{s}^{-1}$ )	kinematic viscosity of air
$\theta$ ( $^\circ$ )	solar PV tilt angle
$\eta_{\text{loss}}$	efficiency loss

upon solar PV cleaning [9]. Moreover, solar PV soiling has also become an important factor that needs to be considered during PV grid integration [10] and the evaluation of solar irradiation potential [11].

Particle deposition and accumulation on solar PV panels are affected by a variety of factors including relative humidity, wind speed, panel tilt angle, and rainfall. Under high relative humidity conditions, hygroscopic particles could be enlarged due to the absorption of environmental moisture [12]. The change in particle size could significantly affect the velocity of particle deposition [13]. Particle deposition also increases with the increase of wind speeds due to an enhanced effect of turbulent deposition [14]. The tilt of PV panels reduces particle deposition and thus the efficiency loss by soiling [15]. Elminir et al. found that the particle deposition density was  $15.84\text{ g/m}^2$  for a tilt angle of  $0^\circ$  and decreased to  $4.48\text{ g/m}^2$  for a tilt angle of  $90^\circ$  based on a seven-month experiment in Egypt [16]. Mejia and Kleissl found that the average soiling losses for a tilt angle smaller than  $5^\circ$  are five times of that for a tilt angle larger than  $5^\circ$  in California [17]. Lu and Zhao [18] found that the tilted angles of  $25^\circ$ ,  $40^\circ$ ,  $140^\circ$  and  $155^\circ$  corresponded to the maximum deposition rates of 14.28%, 13.53%, 6.79% and 9.78%, respectively.

To design effective protocols for solar PV cleaning, it is critical to understand the temporal impacts of solar PV soiling on the efficiency degradation of PV modules. Empirical models (e.g., [19,20]) have been developed based on the regression analysis or artificial Neural Network modelling of experimental data of a specific region. These models have the advantages of being simple, straightforward, and easy to use. However, they are highly contingent upon existing experimental data and are hard to be applied to other regions with different environmental and meteorological conditions from the region where the model was based on. CFD simulation (e.g., [21]) has also been used to study the process of solar PV soiling, which, however, has a high requirement on computational resources. As a promising alternative, mechanistic models could be developed by combining the prediction of particle deposition with the relationship between particle deposition density and solar PV efficiency loss. These models have the advantage of being applicable to a wide range of regions. One such model was proposed by [22] to estimate the cleaning frequency for dirty solar modules. However, this model was based on an empirical model for ‘indoor’ particle deposition [23] which are generally subject to different environmental conditions from outdoor particle deposition.

There is still lack of mechanistic models that are specifically designed to predict the temporal solar PV soiling under outdoor environmental conditions. Especially, such models need to be able to consider the effect of relative humidity on particle deposition. On the

other hand, to develop an economically sustainable solar PV cleaning protocol, it is critical to predict the optimum cleaning interval or frequency from a system perspective. Existing studies estimated the optimum cleaning interval by matching the cleaning-related cost with the energy output loss by soiling [24]. This method, however, did not consider system-level economics and the time value of money. Hence, a system-level economic analysis is needed to evaluate the economics of cleaning plans, which has rarely been done but will allow investors to make informed decisions about when to conduct the cleaning to optimize the profitability of solar PV systems.

In this work, we propose a solar PV soiling prediction model based on the theoretical modelling of particle deposition. The effects of meteorological factors (e.g., relative humidity and precipitation) on solar PV soiling are considered. The economic impacts of solar PV soiling and cleaning are evaluated based on a system-level economic analysis. The optimal cleaning interval is determined by minimizing the relative net-present value (NPV) change. The model is then used to predict and compare the soiling-induced efficiency and economic losses of solar PV modules in seven cities (i.e., Taichung, Tokyo, Hami, Malibu, Sanlucar la Mayor, Doha, and Walkaway) where solar PV has been extensively deployed.

## 2. Methodology

### 2.1. Particle deposition model

Outdoor particle deposition could be considered to be driven by two mechanisms, i.e. gravitational settling as well as wind turbulence and boundary layer effects [25]. Correspondingly, the atmosphere beneath a convenient reference height (e.g., 20 m) was segregated into two layers [26]: (a) an upper layer where particle transport was governed by an atmospheric turbulence resistance term and (b) an underlying quasi-laminar layer where particle transport was governed by Brownian diffusion and inertial impaction that could be grouped into a quasi-laminar resistance term. In this case, particle deposition could be modelled by a resistance in parallel model including two pathways, i.e. atmospheric turbulence and quasi-laminar layer mass transfer, and sedimentation (Fig. 1) [25].

The total deposition velocity  $V_d$  could be expressed as

$$V_d = \frac{1}{R_{at} + R_b} + V_s \cos\theta \quad (1)$$

where  $R_{at} = \frac{1}{C_{DS}U}$  accounts for the atmospheric turbulence resistance term in the upper layer with  $C_{DS}$  being the surface drag coefficient and  $U$

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