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A Review on Modeling and Prediction of Soiling on Solar Photovoltaics and Thermal Collectors

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ABSTRACT

Soiling of solar photovoltaic and thermal collectors can significantly reduce energy output, with losses reaching up to 78% in total yield and more than 1% per day in arid regions. Accurate soiling prediction is essential for optimizing system performance, minimizing downtime, and reducing operational expenses. This review critically examines empirical, analytical, and machine learning-based models used to forecast soiling effects. Empirical models, including transmittance loss and particulate matter-based approaches, report errors between <2% and 14%, while regression models show higher inaccuracies ranging from 40% to 93%. Analytical models such as the Bergin and Toth frameworks provide structured physical estimations but often require calibration and may overestimate under certain conditions. Machine learning and deep learning models demonstrate superior predictive performance, with image-based approaches achieving F1 score of 0.913 and models integrating environmental and image data reaching up to 97% accuracy. Despite these advancements, challenges remain, including limited availability of high-quality data, lack of generalizability across different climates, and insufficient real-time adaptability. This review also explores soiling mitigation strategies such as self-cleaning coatings, automated cleaning systems, and environmental monitoring tools. It emphasizes the need for hybrid, adaptive frameworks integrating artificial intelligence and Internet of Things technologies for improved accuracy and operational efficiency.

1. Introduction

Soiling, the accumulation of dust, pollutants, and organic matter on the surfaces of solar photovoltaics (PVs) and thermal collectors, significantly impacts the efficiency and performance of solar energy systems. This phenomenon leads to reduced energy output, increased maintenance costs, and overall system degradation, particularly in regions with high dust accumulation [1]. Predicting and understanding soiling patterns is crucial for optimizing energy yield, reducing operational costs, and ensuring long-term reliability of solar power system [2].

PV systems convert sunlight directly into electricity using semiconductor materials like silicon. They are widely used in grid-connected and off-grid

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applications, including rooftop installations and large-scale solar farms [3]. Solar thermal collectors, on the other hand, capture sunlight to generate heat for water heating, space heating, or industrial processes [4]. Both technologies are key to renewable energy systems, offering clean, scalable, and sustainable energy solutions. However, their efficiency is significantly affected by environmental factors, particularly dust accumulation [5].

Dust on solar PV panels blocks sunlight, reducing energy generation and causing power losses of up to 78%, depending on dust type and local conditions [6, 7]. Studies have shown that nonuniform soiling can cause local hotspots, leading to long-term PV module failure and a power output reduction of up to 30% [7]. Experimental studies have further demonstrated that different types of soiling, such as dust, leaves, and rainfall, have varying impacts on power loss, with leaves causing the most significant reduction at 38% [8]. Similarly, dust on solar thermal collectors impacts the optical efficiency [9], heat absorption and system efficiency, leading to a drop in the temperature of the heat transfer fluid. These efficiency losses increase maintenance costs, as regular cleaning is required to maintain optimal performance [10]. Regions with high dust levels, such as arid and semi-arid areas, face greater challenges [11].

Accurate soiling assessment is essential for optimizing maintenance strategies, as it helps in determining the most effective cleaning schedules and reducing unnecessary interventions. Predictive modeling plays a crucial role in this by forecasting soiling impacts, enabling proactive maintenance and minimizing operational costs associated with performance degradation and system downtime [10].

This review aims to evaluate and analyse existing soiling prediction models. While various soiling prediction models exist, including empirical, analytical, and machine learning-based approaches, they often lack accuracy, generalizability across diverse environmental conditions, or real-time adaptability [12]. Current models either oversimplify soiling dynamics or require extensive calibration, limiting their practical applicability. Previous studies on soiling prediction for solar photovoltaic and thermal collectors have primarily focused on specific modeling techniques. While these investigations have provided valuable insights, they often lack an integrated framework that comprehensively review multiple predictive models.

The novelty of this work lies in its comprehensive evaluation of existing soiling models, highlighting their strengths and limitations while identifying critical research gaps. Unlike previous reviews that concentrate on isolated modeling techniques, this study systematically synthesizes recent developments across empirical, analytical, and AI-driven methodologies. Therefore, the present review underscores the urgent need to develop multi-factor, adaptive prediction frameworks that incorporate continuous data streams and real-time monitoring through IoT integration. These advances are intended to support the solar energy community in optimizing maintenance strategies and enhancing the reliability, efficiency, and cost-effectiveness of solar power generation systems.

The paper is structured to provide a comprehensive review of the modeling and prediction of soiling effects on solar PV and thermal collectors, with a focus on advances, challenges, and future research directions. It begins with an Introduction that sets the context for the study, outlining the importance of accurate soiling prediction for optimizing solar system performance and maintenance. A section on Mechanisms and Factors Affecting Soiling follows, detailing the sources, environmental influences, and regional variability in soiling accumulation. The paper then delves into Soiling Models, reviewing the various approaches; empirical, analytical, and machine learning-based, used to predict soiling effects. Following this, a section is included on Model Performance Comparisons, followed by a section outlining the Integration of Soiling Models into Performance Forecasting, discussing how soiling models are used to predict energy yield and guide maintenance decisions. The paper also highlights the Economic Analysis of Soiling, and the Uncertainties, Challenges, and Future Improvements in soiling prediction, identifying key sources of error and suggesting improvements for model accuracy. Finally, the Conclusion summarizes the key findings and outlines implications for the solar industry, emphasizing the need for further research to enhance soiling mitigation and prediction methodologies.

2. Mechanisms and Factors Affecting Soiling

2.1. Sources and Composition of Soiling

The primary source of soiling includes mineral dust, which varies in concentration based on geographic location and environmental conditions [13, 14]. Pollen and soot are significant contributors, with organic particles exhibiting higher adhesion to surfaces due to their chemical properties [15, 16]. Areas with high traffic contribute hydrocarbons and other pollutants, enhancing particle adhesion through chemical interactions [16]. Industrial activities and vehicle emissions contribute to particulate matter (PM) in the atmosphere, which settles on PV panels and thermal collectors, obstructing sunlight and diminishing performance. Haze from industrial emissions can reduce solar irradiance by up to 80%, severely affecting PV output [17]. In China, air pollution has led to a decrease in PV capacity factors, with reductions of up to 16.51% observed in certain regions [18]. Reducing emissions from residential and transportation sectors could significantly enhance PV energy generation, with potential increases of 10.3 TWh in China alone [19]. While industrial emissions and vehicle exhaust pose challenges to solar energy efficiency, advancements in air quality regulations and technology may offer pathways to mitigate these impacts, promoting a cleaner energy future.

Dust particles often consist of silica, clay, and other minerals, which affect their physical properties and adhesion potential [13, 14]. The size of particles influence how they interact with the PV surface. Fine particles (less than 3 µm), such as carbon and cement dust, significantly degrade PV performance due to their strong adhesion and high light absorption. In contrast, coarse particles (greater than 3 µm) mainly contribute to mass deposition on PV surfaces, leading to substantial soiling losses, up to 12% per week in some regions [20, 21].

The chemical composition of dust particles plays a pivotal role in determining the severity and persistence of soiling on solar PV and thermal collectors. Studies show that organic-rich and carbon-based particles, such as pollen and graphite, exhibit significantly higher adhesion forces to glass surfaces due to their surface energy characteristics, leading to greater attachment efficiency and reduced removability during the cleaning process [15]. Mineralogical components like silica, calcite, and clays can promote cementation under dew or humidity, causing particles to harden and become resistant to natural or manual cleaning [13]. In Mediterranean environments, dominant dust elements such as silica and calcite have been linked to reduced optical transmittance by up to 75%, correlating with significant PV performance drops [22]. While the focus is often on the detrimental effects of soiling, some studies suggest that understanding the specific composition of dust can lead to tailored cleaning techniques that minimize energy losses and maintenance costs [10].

2.2. Environmental and Climatic Factors

Climatic conditions affect dust deposition rates, which in turn impact the efficiency and power output of PV systems. Higher humidity levels increase the adhesion of dust particles to the panel surface, leading to greater soiling accumulation and reduced energy output [23]. In contrast, lower humidity can facilitate easier cleaning of panels, thereby enhancing their performance [24]. Increased wind speed can reduce dust deposition on solar panels, as it helps to dislodge accumulated particles [23]. Wind direction also plays a role; prevailing winds can either carry dust away from or towards the panels, affecting soiling rates [25]. Studies indicate that high dust densities can lead to significant power reductions, with energy output decreasing by up to 40% due to prolonged soiling [23]. The relationship between these climatic factors and soiling is site-specific, necessitating tailored cleaning strategies for optimal performance [24]. Although humidity and wind are widely known to exacerbate soiling, they also present opportunities for natural cleaning mechanisms, such as rainfall, which can mitigate dust accumulation and improve panel efficiency [25].

Rainfall is a natural cleaning agent for solar panels, but its effectiveness depends on frequency, intensity, and environmental factors. Heavy rainfall is more effective at removing dust and debris, while light rain may redistribute contaminants, leading to further accumulation [26]. Frequent rainfall correlates with reduced soiling levels, as observed in studies where the minimum transmittance loss occurred during periods of high rainfall frequency [27]. Higher intensity rainfall (50-100 mm) significantly improves the cleaning effect, increasing PV output power by 16.1% to 28.2% compared to light rainfall [28]. However, a minimum intensity threshold must be met for effective cleaning; lighter rains often fail to remove accumulated dust [26].

Soiling of solar PV systems varies significantly with seasonal changes and geographic location, impacting energy generation efficiency. Studies show that desert regions experience higher soiling rates due to abundant dust and infrequent rainfall, leading to daily energy losses exceeding 1% [29]. Geographic factors, such as proximity to unpaved roads, also contribute to non-uniform soiling, which can reduce performance across large-scale PV installations [30].

Seasonal variations influence dust accumulation patterns, with summer months typically exhibiting increased soiling due to dry conditions and higher atmospheric dust concentrations [31]. The impact of different environmental variables is summarised in table 1, in which high airborne dust concentration reduces transmittance, causing up to 1% daily power loss, while low wind speeds increase soiling. Wind direction affects dust deposition, especially on aligned panels. High humidity promotes particle adhesion and caking, worsening soiling, whereas rainfall can either redistribute dust (light rain) or effectively clean panels (heavy rain). Temperature variations reduce dust buildup via thermophoresis, while longer exposure times lead to greater soiling. Additionally, horizontal panel installations experience higher dust accumulation, causing significant efficiency losses.

Figure 1 categorizes factors affecting soiling including environmental and geographical [32], installation geometry & panel surface properties, and operational & seasonal factors. Environmental factors include dust type, rainfall, temperature, humidity, and wind, which influence dust accumulation and removal. Geographical factors cover topography, altitude, and urban/rural settings, affecting dust deposition patterns. Installation-related factors such as tilt angle, panel spacing, surface properties, and tracking mechanisms determine how much dust accumulates. Operational & seasonal factors involve cleaning frequency, methods, windstorms, temperature fluctuations, and seasonal variations, all impacting soiling dynamics and mitigation strategies.

Table 1. Impact of Environmental Variables on Soiling of Solar Collectors

Environmental Variable	Impact on Soiling	Source
Airborne Dust Concentration	Higher dust levels reduce transmittance and solar irradiation, leading to a performance drop of up to 1% per day.	[13]
Wind Speed	Increased wind speeds reduce dust accumulation on PV surfaces by promoting particle resuspension and removal, while lower wind speeds lead to higher soiling rates.	[33, 34]
Wind Direction	Arrays aligned with the wind may experience more soiling due to direct dust transport.	[35]
Relative Humidity	High humidity leads to particle adhesion, causing cementation and caking, worsening soiling.	[13, 36]
Rainfall	Light rain can redistribute dust, but heavy rain effectively cleans panels, reducing soiling.	[37]
Temperature	Higher temperature differences between the module surface and surrounding air can reduce dust accumulation due to thermophoresis.	[38]
Exposure Time	Longer exposure times correlate with greater soiling.	[39]
Installation Geometry	Horizontal surfaces experience a decrease in transmittance due to soiling, with significant power generation losses.	[40]

2.3. Differences in Soiling Behavior Between PV Modules and Thermal Collectors

Differences in soiling behaviour between PV modules and thermal collectors arise primarily from their distinct optical requirements and system configurations. PV modules, which convert light directly into electricity, suffer from general light attenuation due to dust accumulation. In contrast, Concentrating Solar Thermal (CSP) collectors, especially those using mirrors or lenses, require precise focusing of sunlight, making them far more sensitive to scattering caused by even minor dust deposits. As a result, CSP systems can experience performance losses 3 to 14 times higher than PV systems under similar soiling conditions [41, 42].

PV modules in arid climates can suffer substantial power losses due to soiling, with daily soiling ratios reaching 0.70 - 0.73 for poly-Si and CdTe technologies [43]. Different PV technologies show varying responses to soiling, with mono-Si modules outperforming poly-Si in overall efficiency but experiencing greater soiling-related losses [44].

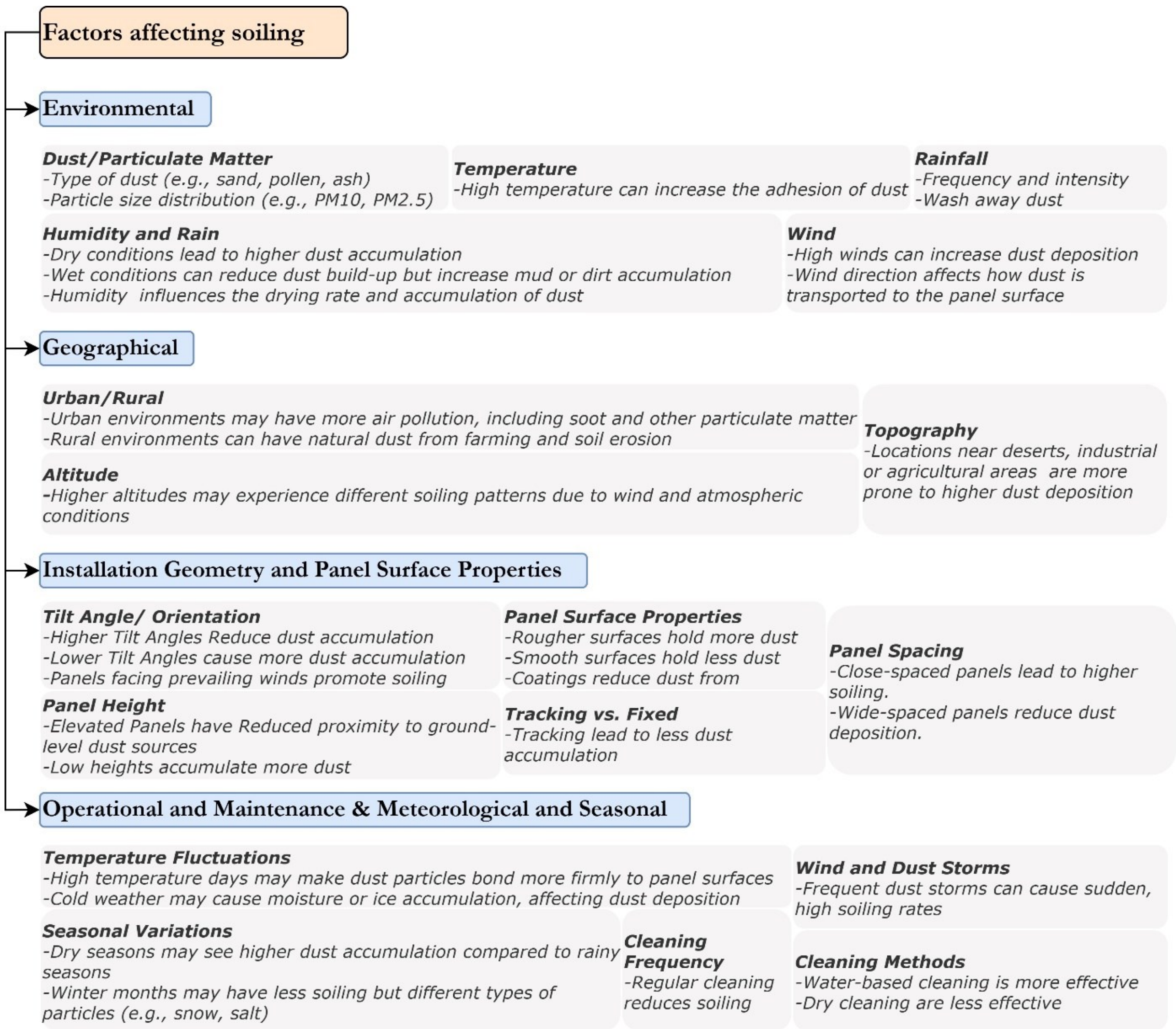

Figure 1. Factors influencing soiling on solar collector surfaces. These factors affect dust accumulation and adhesion, impacting solar collector performance and efficiency

3. Soiling Models

Modeling is essential for estimating energy losses and optimizing cleaning schedules for PV modules and thermal collectors [45]. Recent studies have introduced various approaches to quantify energy reduction caused by factors like dust accumulation and shading, which enables more accurate predictions of system performance [46]. These models simulate different cleaning scenarios to determine optimal cleaning intervals that maximize energy output while minimizing maintenance costs [47].

Figure 2 illustrates the classification of soiling models into Empirical, Analytical, and Machine Learning & AI approaches. Empirical models rely on experimental data and statistical methods, such as transmittance loss, particulate matter analysis, and regression techniques [14, 48]. Analytical models, on the other hand, use physical principles and theoretical formulations to predict the effects of soiling [49, 50]. Machine Learning & AI models apply various techniques, including supervised, unsupervised, and reinforcement learning, to dynamically analyze and mitigate soiling impacts [37]. This classification assists in choosing the most appropriate modeling approach based on available data and computational requirements.

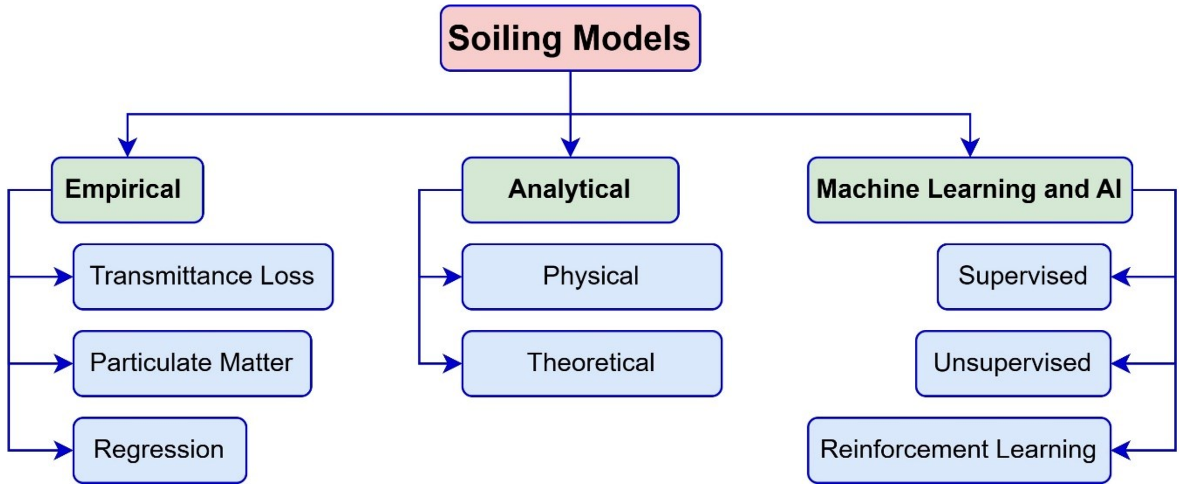

Figure 2. Different classifications of soiling models

However, it is important to note that the boundaries between different soiling models are often non distinct. For example, machine learning and AI-based models, which are primarily data-driven, can, in certain contexts, be classified under empirical modeling [51, 52]. Similarly, analytical models that derive inputs from physical measurements may also exhibit characteristics of empirical models. In this study, a model is classified as empirical when measured data is directly used to establish relationships without the application of additional complex algorithms. Conversely, a model is categorized as analytical when it incorporates theoretical frameworks, analytical equations, or computational algorithms in the modeling process.

This distinction is essential, despite the empirical basis of many models, because the choice of approach affects the accuracy, generalizability, and computational complexity of predictions. Analytical models integrate fundamental physical laws, making them more adaptable to different conditions. AI and machine learning models, although empirical, utilize pattern recognition capabilities that go beyond simple curve fitting, enabling adaptive learning from diverse datasets. Thus, while empirical measurements form the foundation of most soiling models, the classification system reflects the dominant methodology used to derive insights and make predictions.

3.1. Empirical or data driven Models

Empirical or data-driven models are typically based on observed data. However, their accuracy can be limited when applied to different geographical locations, as they may overestimate certain parameters if developed using data from regions with varying environmental conditions [53]. Despite this limitation, empirical models provide a foundational understanding of soiling impacts and are useful for initial system design and optimization.

Empirical soiling models typically describe soiling behaviour as a function of environmental, operational, and surface material factors. Models incorporate variables such as dust concentration, rainfall, wind speed, and the tilt angle of solar collectors [55–57]. Empirical models tend to be easier to implement because they rely on experimental data rather than requiring a deep understanding of the physics of adhesion [58]. The main categories of these models include time-dependent accumulation models, cumulative dust deposition models, and models based on local environmental factors such as wind speed, solar radiation, and humidity [54].

One of the most applied empirical approaches is the time-dependent soiling accumulation model, which describes the accumulation of dust over time, often assuming an exponential or linear growth pattern [59, 60]. The rate of dust accumulation in such models is typically influenced by environmental factors like wind speed, rainfall, and local dust characteristics [61]. Empirical models provide simplicity and data-driven insights, but they may oversimplify complex interactions, require extensive data, and may be complex to implement.

3.1.1. Transmittance loss models

Soiling on solar PV and thermal collectors, significantly reduces transmittance, leading to efficiency losses in solar energy systems [24]. Models have been developed to predict and quantify these losses [62]. Spectral and single-value transmittance models measure transmittance at specific wavelengths (e.g., 500–600 nm) to estimate soiling losses, tailored to the preferred spectral regions of different PV technologies [63]. Transmittance loss models, for instance, correlate dust mass with reduced solar radiation reaching PV panels [64]. For instance, Elminir et al. [65] examined how dust accumulation affects the transmittance of glass covers on solar collectors in arid climates. The results showed a clear link between dust deposition and reduced transmittance. As dust increased from 15.84 g/m² (0° tilt) to 4.48 g/m² (90° tilt and 135° azimuth), transmittance dropped from 52.54% to 12.38%. Hegazy [66] investigated the impact of dust on solar transmittance. The results also showed a strong correlation between dust deposition, tilt angle, and transmittance reduction, with empirical correlations developed to quantify these effects.

3.1.2. Particulate Matter (PM) Deposition-Based Models

Various models have been developed to predict and analyze the impact of PM deposition, each offering unique insights into the factors influencing soiling and its mitigation [67–69]. Simple models predict soiling losses by considering ambient PM concentrations, such as PM_{10} and $PM_{2.5}$, along with factors like PV array tilt and rainfall [70]. These models estimate soiling over time by analysing the relationship between PM levels, dust accumulation, and rain removal [71]. A study by You et al. [49] established a direct relationship between dust mass and PM concentration, demonstrating how increases in particulate levels correlate with greater soiling impacts. Validated against measured data, these models demonstrate the ability to simulate soiling accurately, providing a practical tool for assessing soiling impacts in real-world scenarios [70].

Some models adopt a comprehensive approach by integrating multiple factors into a single framework, considering the entire "dust life cycle" from generation to removal. These models emphasize the interaction between dust particles and solar collector surfaces, aiming to provide a holistic understanding of soiling processes [10]. Additionally, models like the Community Multiscale Air Quality (CMAQ) model simulate PM dry deposition and analyze its impact on PV performance across different locations, offering a broader perspective on soiling effects [67].

3.1.3. Regression models

Regression models play a crucial role in soiling modeling of solar panels by providing predictive capabilities that enhance the understanding and management of soiling effects on PV performance [72]. These models help in estimating the extent of soiling, which is essential for optimizing cleaning schedules and improving energy production efficiency [72]. Equation (1) is the general form of a regression model where y is the dependent variable. $x_1, x_2, \cdots$ are the independent variables. β_0 is a constant term while β_1, β_2, ..., β□ are the coefficients, representing the impact of each independent variable on the dependent variable. ϵ is the error term, accounting for the difference between the actual and predicted values of y.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \tag{1}$$

The work of Guo et al. [73, 74] significantly advanced this field by exploring the relationships between soiling metrics and key environmental variables such as relative humidity, wind speed, and PM_{10} concentrations. Their studies revealed how these factors interact to influence the extent of soiling, providing a quantitative basis for predicting maintenance needs in various applications, from solar panels to building facades.

A study by Kaiss and Hassan [75] employed a regression approach to model dust deposition rates on ground-mounted PV panels, considering factors such as dust diameter, wind speed, and tilt angle. Results showed that dust diameter had the greatest impact, followed by tilt angle and wind speed. The final regression model, with an R^2 of 82.75%, indicated a positive correlation between dust diameter and deposition rate, while higher wind speeds reduced deposition due to turbulence.

3.2. Analytical Models

Analytical models for solar collector soiling are crucial for quantifying the impact of dust accumulation on solar energy systems. These models can be divided into physical models and theoretical models [13, 76]. However, these models tend to overlap in practice and hence it is often uncommon to find a purely physical or theoretical model. Physical models focus on the physical processes of dust deposition and removal [77]. These models provide mathematical formulations to estimate the energy losses caused by soiling and often integrate environmental data with optical and electrical properties of solar collectors [2, 78, 79].

Analytical models account for multiple deposition mechanisms, including gravitational settling, inertial impaction, Brownian diffusion, electrostatic attraction, and turbulent deposition, and often incorporate environmental parameters such as wind speed, humidity, and particle properties to enhance predictive accuracy [80].

3.2.1. The Bergin Model

The Bergin model is a physics-based approach designed to estimate soiling losses in PV panels caused by PM deposition [81]. It assesses the impact of different PM species such as dust, organic carbon and black carbon on transmittance losses, calculating the total mass of each deposited component. The model expresses transmittance loss per unit of deposited mass, incorporating parameters like mass absorption efficiency and scattering properties to quantify soiling effects. It assumes a linear relationship between transmittance loss and mass loading. The Bergin model offers a structured methodology for evaluating PV soiling but requires adjustments based on empirical observations to improve reliability in specific conditions. The Bergin model is shown in equation (2) where $\frac{\Delta\tau}{PM_F}$ is the transmittance loss per unit mass, i is the different species of particulate matter (PM). PM_F is the total PM loading in a specific time period. β_i, $E_{\text{scat},i}$ and $E_{\text{abs},i}$ respectively represent the up-scatter fraction of the PM, mass scattering efficiency, and the efficiency of mass absorption.

$$\frac{\Delta\tau}{PM_F} = -\frac{1}{PM_F}\sum_{i=1}^{n}\left(E_{\text{abs},i} + \beta_i E_{\text{scat},i}\right) PM_{F,i} \quad (2)$$

The Bergin model's performance in estimating soiling losses on photovoltaic panels was investigated by Bessa et al. [82] in Jaén, Spain, and it showed limitations, particularly in overestimating losses during dry periods. The model was also sensitive to environmental factors, especially organic carbon concentrations, which led to overestimation due to the scattering of solar radiation.

3.2.2. The Toth Model

The Toth model shown in equation (3), was designed to estimate daily soiling losses on PV panels, using PM concentration and rainfall as key environmental parameters [83]. The model calculates cumulative soiling losses by summing the PM concentration over time, with constants A_1 and A_2 determined through a Truncated Newton Algorithm. A critical assumption of the Toth model is that only coarse particles ($PM_{10-2.5}$) are removed during rainfall, while smaller particles ($PM_{2.5}$) are considered sticky and not washed off, which may cause inaccuracies, particularly in areas with high concentrations of fine particles. The Toth model tends to overestimate soiling losses during dry periods when fine particles are abundant [82]. While valuable, the model's reliance on specific assumptions about particulate matter behaviour suggests the need for caution when applying it in various geographical contexts.

$$r_s = 1.0 - \left(A_1 F_d + A_2 C_d\right) \tag{3}$$

Where F_d and C_d represents the cumulative soiling losses.

3.2.3. The You/Saiz model

You et al. [49] developed a model based on particle deposition, which accounts for an efficiency loss of 0.0139% per gram of deposited dust [84]. The You/Saiz model estimates the efficiency loss of PV panels due to dust and pollen accumulation, using a coefficient derived from Saiz et al. [85], which suggests a 3.8% efficiency loss per gram of deposited material. The model shown in equations (4) – (6) incorporates environmental factors such as deposition velocity (V_d), PM concentrations ($PM_{2.5}$ and PM_{10}), and the number of days without rainfall (N_D), to calculate the dust deposition density and overall efficiency loss. The final equation integrates these parameters, making the model adaptable to different regions. The You/Saiz model is a reliable and adaptable tool for estimating soiling impacts on PV panel efficiency, offering accurate predictions based on local environmental conditions [82]. In this model, the dust deposition density is given by equation (4) and the soiling ratio, r_s is given by equation (6).

$$\omega = V_{\mathrm{d}} \cdot PM \cdot N_{\mathrm{D}} \cdot 10^{-6} \tag{4}$$

$$\eta_{\mathrm{loss}} = 0.0139 \cdot \omega \tag{5}$$

$$r_{\mathrm{s}} = 1 - 0.0385 \cdot \omega \tag{6}$$

3.2.4. The Coello Model

The Coello model estimates soiling losses on PV systems by incorporating environmental factors such as PM concentration, deposition velocity, rainfall, and PV tilt angle [70]. The model assumes that soiling results from atmospheric particle deposition and it calculates dust accumulation over time using these parameters, generating a time series of cumulative mass deposition to assess long-term soiling effects. The model also evaluates transmission losses based on the soiling ratio and includes a reset mechanism triggered by rainfall to account for dust removal. By integrating these elements, the Coello model (equations 7 - 8) provides a structured approach to understanding soiling impacts on PV efficiency under varying environmental conditions.

$$m = \left(v_{10-2.5} \cdot P_{10-2.5} + v_{2.5} \cdot P_{2.5}\right) \cdot t \cdot \cos\beta \tag{7}$$

$$1 - r_{\mathrm{s}} = 0.3437 \cdot erf\left(0.17 \cdot \omega^{0.8473}\right) \tag{8}$$

Where m is the mass accumulation per time step (g/m²), determined by the deposition velocity (v) in meters per second (m/s), the ambient particulate matter concentration (P) in grams per cubic meter (g/m³), and the time step (t) in seconds. The PV system's tilt angle (β) also influences deposition. Particles with aerodynamic diameters between 10 and 2.5µm are denoted by the subscript *10–2.5*, while those smaller than 2.5µm are indicated by the subscript *2.5*.

3.2.5. Computational Fluid Dynamics (CFD) Models

CFD models for solar collector soiling focus on understanding the interactions between dust deposition and the performance of solar PV systems [86, 87]. These models simulate airflow, dust particle behaviour, and their effects on energy yield and have been applied to study soiling and performance optimization in solar collectors [88]. CFD simulations can predict dust deposition on PV modules, considering factors such as wind direction, tilt angle, and orientation [89–91].

Dust deposition is usually analysed using the Reynold Averaged Navier Stokes (RANS) equations coupled with the Discrete Phase Model (DPM) [87]. The RANS equations are used to describe the motion of fluid flows, especially turbulent flows. They are derived by decomposing the flow variables into mean and fluctuating components. The RANS equations for incompressible flow are shown in equation (9) [92].

$$\frac{\partial \overline{u_i}}{\partial t} + \overline{u_j}\frac{\partial \overline{u_i}}{\partial x_j} = -\frac{1}{\rho}\frac{\partial \overline{p}}{\partial x_i} + \nu \frac{\partial^2 \overline{u_i}}{\partial x_j^2} + \frac{\partial \tau_{ij}}{\partial x_j} \tag{9}$$

Where; $\overline{u_i}$ is the time-averaged velocity component in the i-th direction, $\overline{p}$ is the time-averaged pressure, ρ is the fluid density while ν is the kinematic viscosity. τ_{ij} is the Reynolds stress tensor, representing the effect of turbulence, and is defined as $\tau_{ij} = \overline{u_i^{'} u_j^{'}}$, where $u_i^{'}$ are the fluctuating velocity components.

3.2.6. Soiling as a Function of Total Radiation of PV Panel

Shukla et al. [93] developed a model which quantifies the impact of dust on the total radiation received by a PV panel, crucial for predicting efficiency loss due to soiling. It accounts for three radiation components: direct radiation, diffuse radiation, and reflected radiation. The model (equation 10) mathematically incorporates factors such as anisotropy index (A_i), PV module slope (β), horizontal brightening factor (*f*), and ground reflectance (ρ) to determine effective radiation under dusty conditions. By analysing how dust alters radiation components, the model aids in optimising PV system performance in dusty environments and improving energy yield predictions. With θ being the angle of incidence of solar irradiance, the ratio $\phi_{dr} = \frac{\cos\theta}{cos\theta_z}$ represents the comparison between the direct (beam) radiation incident on a tilted surface and the direct radiation falling on a horizontal surface.

Studies by Khalid et al. [94] indicate that this model is instrumental in quantifying the reduction in power output due to dust. For instance, it was noted that dust accumulation can lead to a power output reduction of 6.5% in Athens, 17.4% in Egypt, and varying percentages in other regions, such as 10% in the UAE and 4%-15% in Spain.

$$R_T = \left(R_{dr} + R_{df} A_i\right)\phi_{dr} + R_{df}\left(1 - A_i\right)\left[\frac{1-\cos\beta}{2}\right] + \left[1 + f\sin^3\left(\frac{\beta}{2}\right)\right] + R_\rho\left[\frac{1-\cos\beta}{2}\right] \quad (10)$$

3.2.7. Bilinear Model

The Bilinear Model [95] of PV power generation mathematically represents the relationship between solar irradiance and the power output of dust-affected PV panels. It establishes a bilinear relationship to assess efficiency loss due to dust accumulation. This model is particularly useful in dusty environments for predicting performance degradation and optimizing PV system design. Compared to other models, it balances complexity and practicality, making it a valuable tool for managing solar energy systems in soiling-prone conditions. Equation (11) is applied where the solar irradiance level G < 200 W/m^2 and equation (12) is applied where G > 200W/m^2.

$$P = P_r\left[\frac{G}{G_r}\left[1 + \beta\left(T_C - T_r\right)\right] - S\left[1 - \left(1 - \frac{G}{200}\right)^4\right]\right] \quad (11)$$

$$P = P_r\left[\frac{G}{G_r}\left[1 + \beta\left(T_C - T_r\right)\right] - S\left(\frac{G_r - G}{G_r - 200}\right)\right] \quad (12)$$

Where, G_r , T_r , P_r are respectively the Standard Test Conditions (STC) reference parameters for solar irradiance, temperature and power. S represents the solar irradiance levels, β is the temperature coefficient, and T_C denotes the computed temperature.

3.2.8. Dust Deposition Effected PV Output Power Model

The Effected PV Output Power Model [96] quantifies the impact of dust accumulation on PV panel performance. It calculates power loss due to soiling by modeling power output as a function of solar radiation and dust accumulation. Key factors include total radiation received, G(W/m^2), soiling loss index, and energy conversion efficiency, all of which influence energy production. The model helps analyze performance degradation, optimize cleaning schedules, and improve maintenance strategies. It is particularly useful for designing and managing PV systems in dust-prone areas to maximize efficiency and energy yield. This model is shown by equation (13), where $P_{PV}\left(W\right)$ is the dust deposition effected PV output power of a PV module of rated power $P_r\left(W\right)$ derated at $\eta_d\left(\%\right)$. The temperature coefficient of the PV module is β (%/°C). T_c and T_r respectively represent the measured PV temperature and the reference temperature at STC in (°C). G_r (W/m^2) is the reference irradiance at STC.

$$P_{PV} = P_r \eta_d \left[1 + \beta\left(T_C - T_r\right)\right]\left(\frac{G}{G_r}\right) \quad (13)$$

3.2.9. Energy Conversion Efficiency of a Dust Accumulated PV Panel Surface

A model developed by Fan et al. [97] shown in equation (14) suggested that the energy conversion efficiency of PV panels is crucial in determining their effectiveness in converting sunlight into electricity. When dust accumulates on the panels, it can reduce this efficiency. The efficiency (η) is mathematically represented by the ratio of PV output energy $\left(P_{out}\right)$ to input energy from solar irradiance (G_e). Dust accumulation impacts both the output voltage (V) and current (I), leading to reduced efficiency by blocking sunlight and decreasing solar irradiance (G). A soiling loss index quantifies this efficiency loss. A_{PV} represent surface area of the PV panel.

$$\eta = \frac{P_{out}}{G_e} = \frac{V \cdot I}{G_{sun} \cdot A_{PV}} \tag{14}$$

3.2.10. Model of the Maximum Power Output of a Soiled PV Module

Al-Addous et al. [98] showed that the maximum power output (P_{max})(W) of a soiled PV module is reduced due to dust accumulation, which impacts its performance. The model to calculate this output incorporates a soiling loss index that quantifies the reduction in power output, expressed as:

$$P_{max} = P_r \left(\frac{G\left(1+S_r\right)}{G_r} \right) \left[1+\beta\left(T-T_r\right)\right] \tag{15}$$

where P_r (W) is the power output at STC. G(W/m^2) is the incident solar irradiance at 30^o while G_r (W/m^2) is the reference irradiance at STC. S_r , β, T and T_r are respectively the soiling loss index, the temperature coefficient of power, the operating temperature and the reference temperature at STC.

3.3. Machine Learning and AI-Based Soiling Prediction

Machine learning (ML) and artificial intelligence (AI) have been increasingly employed for predicting soiling on solar collectors, enhancing the efficiency and reliability of solar power plants [61, 99, 100]. Machine learning and AI-based prediction algorithms can be classified into several categories, primarily based on their learning paradigms and the nature of the output they generate. The main classifications include supervised learning, unsupervised learning, and reinforcement learning, each with distinct algorithms and applications [101–104]. Recent advancements in machine learning and deep learning have introduced sophisticated predictive models, such as SolarQRNN, which use environmental data and panel images to predict soiling losses with high accuracy [105]. These models, integrate regression techniques and computer vision, outperforming traditional approaches [105, 106].

3.3.1. Supervised Machine Learning

Supervised Machine Learning (SML) encompasses a variety of algorithms designed to predict outcomes based on labelled datasets [107]. These algorithms learn from input-output pairs, enabling them to generalize and make predictions on unseen data. The most prominent SML algorithms include Decision Trees, Random Forests, Support Vector Machines (SVM), Naive Bayes, K-Nearest Neighbours (KNN), and Neural Networks [108, 109]. Each algorithm has unique strengths and is suited for different types of problems, such as classification and regression tasks.

Studies have analysed the performance of different ML algorithms. For instance, Lopez-Lorente et al. [110] analysed the performance of the machine learning models which revealed varying degrees of accuracy in estimating soiling losses. Among the ML models, CatBoost demonstrated the highest accuracy when trained with field observations, achieving a mean absolute error (MAE) of 0.88% and an RMSE of 1.25%. When using satellite-derived weather data, CatBoost maintained its leading position with an MAE of 1.10% and an RMSE of 1.55%. LightGBM followed closely, indicating competitive performance with a mean absolute percentage error (MAPE) of 56.1%. XGBoost, while slightly less accurate, reported the least normalized mean deviation error (nMDE) of 5.86%.

The development of DGImNet, by Fang et al. [111], represents a significant advancement in the estimation of PV soiling loss. This deep learning model integrates images of PV panels with time series environmental factors (TSEFs), employing a supervised learning approach on a labelled dataset to enhance predictive accuracy. The model achieved a root mean square error (RMSE) of 0.0406 and a mean absolute error (MAE) of 0.0774 in regression tasks, alongside a 76.59% accuracy and an F1-score of 0.69 in classification tasks with 16 categories.

Various ML and AI algorithms, including artificial neural networks (ANN), Physical Informed Neural Networks (PINN), Long Short-Term Memory (LSTM) networks, XGBoost, random forests, support vector machines (SVM), deep learning architectures, decision trees, convolutional neural networks (CNN), recurrent neural networks (RNN), particle swarm optimization (PSO), gradient boosting machines (GBM), genetic algorithms (GA), k-nearest neighbours (KNN), and ensemble learning techniques, have been used to develop predictive models [112–117].

3.3.2. Unsupervised Machine Learning

Unsupervised learning techniques have gained traction in modeling soiling on solar collectors due to their ability to identify patterns in unlabelled data and enhance predictive maintenance strategies [107]. Various machine learning models, including clustering and anomaly detection, have been explored to estimate soiling effects without predefined labels. Brenner et al. [118] proposed a data-driven approach using Decision Tree models to assess soiling in parabolic trough collectors, achieving an R^2 value of 0.77, thereby improving cleaning schedules and operational efficiency [118]. While supervised models like neural networks and regression techniques have demonstrated accuracy in soiling estimation [119], unsupervised techniques such as clustering can offer cost-effective solutions by reducing dependency on labelled datasets. Additionally, deep learning-based spatial classification models have been used to detect soiling distribution through image processing techniques [120]. However, challenges remain in the real-time adaptation of unsupervised models to varying environmental conditions and different solar collector technologies. Integrating hybrid approaches, such as semi-supervised learning, may further enhance the predictive accuracy and automation of soiling detection systems.

Unsupervised learning techniques offer promising avenues for analysing soiling patterns. Clustering algorithms, such as k-means or hierarchical clustering, could be employed to group similar soiling patterns or conditions, potentially uncovering new insights into the factors influencing soiling [121]. Additionally, dimensionality reduction methods like Principal Component Analysis (PCA) might help identify the most significant features affecting soiling, enabling the development of more efficient cleaning schedules [122].

The integration of edge devices and surveillance cameras, as demonstrated by the SoilingEdge model, could further enhance real-time unsupervised learning applications. By continuously monitoring and analysing soiling patterns, these technologies enable dynamic and adaptive responses to changing conditions [117].

3.3.3. Reinforcement Learning

Reinforcement learning (RL) frameworks rely on predictive models to enhance decision-making, with Artificial Neural Networks (ANNs) playing a crucial role in this process [123]. ANNs have been effective in modeling soiling dynamics on PV panels [124, 125], as demonstrated by a study that achieved an R^2 value of 0.68073 using meteorological data as inputs [112]. Sensitivity analysis further identified relative humidity and wind direction as key factors influencing soiling rates, providing valuable insights for optimizing cleaning strategies. These predictive capabilities make ANNs well-suited for integration into RL systems, where they can support adaptive maintenance decisions.

Beyond ANNs, Decision Tree models have shown strong performance in estimating soiling levels for parabolic trough collectors, achieving an R^2 of 0.77 and improving cleaning recommendations by 12.2% [118]. Other models, such as Random Forest and Multilayer Perceptron (MLP), have also been applied to soiling estimation on PV panels, with MLP exhibiting the lowest error rate [119]. These machine learning models can be incorporated into RL frameworks to refine decision-making and optimize maintenance schedules.

Advanced deep learning techniques, such as convolutional neural networks (CNNs), have been employed to detect soiling through visible spectrum imaging, achieving high F1 scores in classification tasks [121]. Additionally, the SoilingEdge model leverages deep learning for power loss estimation due to soiling, demonstrating robust performance across different hardware platforms [117]. These image-based approaches, when integrated into RL systems, enable real-time monitoring and automated decision-making. By combining machine learning and deep learning techniques with reinforcement learning, it is possible to develop autonomous systems that not only predict and detect soiling but also dynamically optimize maintenance strategies. This integration ultimately enhances the efficiency, reliability, and longevity of solar energy systems.

4. Model performance comparisons

Table 2 summarizes the performance of different soiling models, including empirical, analytical, machine learning and artificial intelligence-based models.

Table 2. Comparison of Different Soiling Models and Their Performance in Solar Collectors

No.	Model Type	Key Insight	Accuracy	Source
1	Transmittance Loss Models	Based on natural soiling experiments, these models showed errors <2%, making them highly accurate for site-specific estimations.	<2% error	[126]
2	Particulate Matter (PM) Deposition-Based Models	Models using PM data showed errors ranging from 4-14%, influenced by cleaning events, making them moderately reliable.	4–14% error	[126]
3	Regression Models (Environmental Parameter-Based)	Models relating soiling to environmental factors had high errors (40-93%), making them unsuitable for general applications.	40–93% error	[126]
4	Analytical Models (Dust Accumulation-Based)	These models use dust deposition rates, environmental factors, and empirical equations to estimate soiling losses.	-	[54]
5	Theoretical Models (Time-Dependent Soiling Effects)	These models attempt to predict the impact of long-term soiling on PV performance but face challenges in accurately modeling real-world conditions.	-	[54]
6	Machine Learning Models (Image-Based Detection)	CNN, SVM, RF models used for soiling detection; CNN achieved the best performance with an F1 score of 0.913.	F1 score: 0.913 (91.3% accuracy)	[121]
7	Supervised Learning (Weather & Operational Data)	MLP model outperformed other ML models (RF, Decision Tree) with the lowest error of 0.0003, making it highly effective.	Error: 0.0003 (high accuracy)	[119]
8	Artificial Intelligence (AI) and Deep Learning (Real-Time Monitoring)-Based Predictive Maintenance	Models using real-time image and weather data can detect soiling with high accuracy, reducing computational costs compared to traditional models.	97% accuracy	[127]

5. Integration of Solar Collector Soiling Models into Performance Forecasting

The integration of soiling models into solar collector performance forecasting has gained significant attention due to the adverse effects of dust accumulation on PV and solar thermal systems. Soiling affects energy yield by reducing the optical efficiency of solar panels, making its accurate prediction essential for improved forecasting. Studies have incorporated machine learning techniques, such as ANNs, to predict soiling rates based on meteorological conditions like humidity and wind direction [112]. Another approach integrates soiling into forecasting models using a digital twin methodology, allowing adjustments to machine learning-based predictions for more accurate power generation estimates [116]. For long-term forecasts,

Monte Carlo simulations have been applied to quantify the uncertainty associated with soiling losses, providing insights into the interannual variability of soiling and its impact on energy production [128]. Additionally, physics-based models have been developed to predict soiling on parabolic trough collector mirrors by considering mechanisms such as gravitational settling, impaction, and Brownian motion [129].

Recent developments have shown potential for integrated models, offering pathways to simultaneously predict and mitigate temperature-induced soiling effects in energy yield forecasting [130]. Furthermore, numerical insights into enhanced heat transport in PCM-based thermal systems, suggest that integrating thermal response models with soiling and performance forecasting could enable more accurate predictions of system behaviour under variable thermal loading [131]. In addition, the integration of predictive soiling models into multi-generation systems, as proposed by Hashemian and Noorpoor [132], could support thermodynamic and thermoeconomic optimizations by accounting for environmental soiling effects on solar collectors.

These findings highlight the necessity of integrating advanced soiling models into performance forecasting to minimize energy losses and optimize cleaning strategies, ultimately enhancing the efficiency and financial viability of solar energy systems. Table 3 presents a summary of selected studies on soiling prediction parameters, highlighting the most critical variables identified as having significant influence on model accuracy.

Table 3. Summary of key studies on soiling prediction parameters for photovoltaic systems, highlighting the most influential variables identified in each model

No.	Source	Prediction Parameters	Important Parameter(s)
1	Kappler et al. [116]	Global Horizontal Irradiance, Power value from the previous day, Solar elevation angle, air temperature, sunny minutes per hour, sun's azimuth angle, wind speed	Global Horizontal Irradiance, power output of the previous day, solar elevation angle
2	Suhaimi et al. [112]	Precipitation, wind angle, ambient temperature, wind speed, transient irradiation	Wind speed
3	Muller & Rashed [128]	Soiling rates, rainfall, irradiance, PV system parameters, soiling variability	Soiling variability
4	Voukelatos et al. [129]	Particle diameter and size distribution, deposition velocity, wind speed and direction, air temperature, aerosol particle concentration, sun position, relative humidity	Wind speed, wind direction

6. Economic Analysis of Soiling

The economic implications of soiling in solar PV and thermal systems are increasingly recognized as pivotal in system design and operational strategies. Soiling reduces power output by diminishing irradiance on panel surfaces, which directly translates into lost revenue and increased maintenance expenditure. Globally, soiling reduces solar power production by at least 3 – 4% annually, resulting in an estimated €3 – 5 billion in revenue losses; this figure could rise beyond €7 billion if mitigation strategies are not enhanced [133].

Economic feasibility is especially critical in regions with high soiling rates, such as the Middle East and North Africa. For instance, a study in Saudi Arabia demonstrated that while soiling significantly reduces PV performance, optimal cleaning intervals can minimize economic losses effectively, underscoring the importance of localized, cost-sensitive cleaning strategies [134].

Techno-economic models have been used to determine cost-optimal cleaning schedules. These incorporate net present value (NPV) analysis and Monte Carlo simulations to assess uncertainties related to cleaning costs, environmental conditions, and electricity tariffs. For example, You et al. [49] developed a framework that showed relative NPV gains of up to 20% when optimal cleaning strategies were employed compared to routine, fixed-interval cleaning. Moreover, the economic burden of soiling is compounded by declining electricity prices, which reduces the marginal gains from additional energy recovery through cleaning. As observed in the U.S. market, the decreasing profitability of cleaning activities has paradoxically led to increased soiling-related energy losses because fewer systems undergo timely maintenance [135].

Innovative mitigation approaches, such as hydrophobic coatings, robotic cleaning systems, and predictive maintenance using AI, are being explored to improve return on investment. While these technologies require upfront capital, their long-term economic viability is favorable, particularly in high-soiling zones. However, regional adaptation remains key; for example, agrivoltaic systems in Chile exhibited a 0.35% daily loss due to soiling, which drastically affected profitability during dry seasons [136].

Soiling imposes a substantial economic burden on solar energy systems, with losses spanning billions annually. Optimal mitigation strategies, tailored to local conditions and powered by predictive analytics, can significantly reduce these losses and enhance system profitability. Future deployment of solar technologies should prioritize integrated economic assessments to balance capital investments with operational savings.

7. Uncertainties, Challenges, Limitations and Future Improvements in soiling modelling

The accuracy of soiling models in solar collectors is significantly affected by environmental variability. Factors such as wind speed, humidity, precipitation, and airborne particulate matter lead to inconsistencies in model predictions. Studies have demonstrated that wind angle and transient irradiation play a crucial role in soiling deposition, making it challenging to develop universal predictive models [112]. Additionally, surface material properties and coating technologies influence soiling accumulation. Research on spectral reflectance loss suggests that different dust compositions and coatings can alter the degradation rates of mirrors and panels [137].

A major challenge in soiling modelling is the lack of standardized datasets for training ML models. Large-scale, publicly available datasets are scarce, making it difficult to generalize models across different climatic conditions [118]. Furthermore, testing protocols for evaluating soiling effects vary, reducing reproducibility in research. To address this, standardized testing frameworks are necessary to validate models under real-world conditions and enhance predictive reliability [79].

Hybrid modelling approaches, integrating empirical, analytical, and AI-driven techniques, offer a promising avenue for improving soiling predictions. Decision tree models and ANNs have shown high accuracy in estimating soiling levels based on operational and meteorological data [118]. Additionally, advancements in self-cleaning surfaces and nanotechnology-based anti-soiling coatings can significantly reduce soiling-related energy losses. These coatings, designed to repel dust and water, enhance optical efficiency and extend the maintenance intervals of solar collectors [72].

The integration of Internet of Things (IoT) sensors for real-time soiling detection is a key research focus. IoT-enabled sensors can provide continuous monitoring of soiling levels, facilitating timely maintenance and optimizing energy output. Furthermore, automated robotic cleaning systems and AI-driven predictive maintenance are being explored to improve efficiency and reduce operational costs [79]. Lastly, the development of climate-specific soiling models tailored to regional atmospheric conditions is crucial for enhancing predictive accuracy and optimizing cleaning schedules [112].

Addressing uncertainties in soiling modelling requires improvements in data availability, model validation, and hybrid analytical approaches. Future advancements, particularly in IoT-based real-time monitoring and self-cleaning technologies, have the potential to enhance solar collector performance and reduce maintenance costs.

8. Conclusion and Future Research Directions

Soiling significantly impacts the efficiency and reliability of solar PV and thermal collector systems by reducing energy yield and increasing operational costs. This review has examined various soiling models, including empirical, analytical, and machine learning-based approaches, highlighting their strengths, limitations, and applicability. While empirical models offer simplicity and direct data-driven insights, they often lack predictive accuracy across diverse environmental conditions. Analytical models incorporate physical principles but require extensive parameter calibration. Recent advancements in artificial intelligence and machine learning have improved prediction accuracy; however, their effectiveness is constrained by data availability and the complexity of real-world conditions.

Some limitations are inherent in the present study; the classification and comparison of models, i.e. empirical, analytical, and AI-based, were based primarily on reported outcomes and methodologies rather than uniform benchmarking or meta-analysis. As such, differences in experimental setups, environmental contexts, and evaluation metrics among the reviewed studies may influence the comparability and generalizability of the conclusions drawn. Additionally, although efforts were made to identify critical research gaps and propose future directions, the evolving nature of the field means that some recent developments or unpublished works may not have been captured. The review also relied heavily on secondary data reported in the original studies, without the opportunity to validate or test the models independently. While the study discusses the integration of soiling models with IoT and machine learning frameworks, these insights are theoretical and not supported by empirical validation within the context of this review. These limitations highlight the need for empirical testing, real-world validation, and standardized evaluation frameworks to support future advancements in this field.

Building on these observations, future research could explore several key areas to address current gaps and enhance the reliability and applicability of soiling prediction models. Despite progress in soiling modeling, several areas require further research and development:

1. *Hybrid Modeling Approaches* – Future studies should focus on integrating empirical, analytical, and AI-based models to enhance predictive accuracy and adaptability across different climatic regions. Combining physics-based insights with data-driven techniques can improve model robustness.

2. *Real-Time Monitoring and IoT Integration* – The integration of machine learning models with Internet of Things (IoT) sensors can enable real-time soiling detection and automated mitigation strategies. Developing cost-effective IoT-based monitoring systems will help optimize maintenance schedules.

3. *Standardized Data Collection and Model Validation* – The lack of standardized datasets and validation frameworks limits the generalizability of soiling models. Establishing global benchmark datasets and testing protocols will enhance model reliability and comparability across different environments.

4. *Advanced Soiling Mitigation Strategies* – More research is needed on novel anti-soiling coatings, self-cleaning materials, and autonomous robotic cleaning systems. Evaluating the long-term effectiveness and economic viability of these solutions will support large-scale deployment.

5. *Economic and Environmental Impact Assessments* – While soiling models primarily focus on energy losses, comprehensive cost-benefit analyses of mitigation strategies are limited. Future research should assess the financial trade-offs between predictive cleaning schedules and energy recovery to inform industry best practices.

6. *Hybrid techniques for soiling prediction* - Given the demonstrated effectiveness of Generalized Regression Neural Networks (GRNN) and Multilayer Perceptron Neural Networks (MLPNN) in related environmental and energy forecasting applications, these models offer considerable promise for future research in the prediction of soiling on solar energy systems. Although GRNN and MLPNN have not yet been widely applied specifically to soiling prediction, their capacity to model complex nonlinear relationships, adapt to diverse environmental variables, and generalize effectively from limited or noisy datasets makes them well-suited for such tasks. Their successful implementation in analogous domains such as wind power forecasting and solar irradiance estimation supports their potential utility in accurately capturing the multifactorial nature of soiling accumulation. Therefore, future studies should consider the application of GRNN, MLPNN, or hybrid models that combine their respective strengths, to develop robust predictive frameworks tailored to varying climatic conditions and dust deposition patterns.

Addressing these challenges will contribute to the development of more effective and scalable soiling prediction and mitigation strategies, ultimately enhancing the sustainability and efficiency of solar energy systems. Future advancements in AI, sensor technology, and material science will play a crucial role in overcoming existing limitations and optimizing solar power generation in diverse environmental conditions.

Nomenclature

A_i	Anisotropy index
β	PV system tilt angle (°)
β_i	Up-scatter fraction of the particulate matter
β_1 , β_2 , ..., β□	Regression coefficients
C_d, F_d	Soiling loss coefficient
ϵ	Error term
$E_{scat,i}$	Mass scattering efficiency (m^2/g)
$E_{abs,i}$	Efficiency of mass absorption (m^2/g)
f	Horizontal brightening factor
G	Total solar radiation received (W/m²)
G_r	Reference solar irradiance (W/m^2)
m	Mass accumulation per time step (g/m²)
N_D	Number of days without rainfall
η	Energy conversion efficiency
θ	Angle of incidence of solar irradiance (°)
θ_z	Solar zenith angle (°)
P	Ambient particulate matter concentration (g/m³)
$PM_{2.5}$, PM_{10}	Particulate matter concentrations (μg/m³)
P_{max}	Maximum power output (W)
PM_f	Total PM loading
P_r	Reference power (W)
ρ	Fluid density (kg/m^3)
r_s	*Soiling ratio (%)*
t	*Time step (s)*
τ_{ij}	Reynolds stress tensor (N,m^2)
T_r	Reference temperature (°C)
$\overline{u_i}$	Time-averaged velocity (m/s)
u_i'	Fluctuating velocity components (m/s)
v	*Velocity (m/s),*
ν	Kinematic viscosity (m^2/s)
V_d	Deposition velocity (m/s)

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