Impact of dust accumulation on photovoltaic panels: a review paper

Haneen Abuzaid, Mahmoud Awad and Abdulrahim Shamayleh

Department of Industrial Engineering, American University of Sharjah, Sharjah, UAE

ABSTRACT
Photovoltaic systems (PV) have been extensively used worldwide as a reliable and effective renewable energy resource due to their environmental and economic merits. However, PV systems are prone to several environmental and weather conditions that impact their performance. Amongst these conditions is dust accumulation, which has a significant adverse impact on the solar cells' performance, especially in hot and arid regions. This study provides a comprehensive review of 278 articles focused on the impact of dust on PV panels' performance along with other associated environmental factors, such as temperature, humidity, and wind speed. The review highlights the importance of modelling dust accumulation along with other ecological factors due to their interactive nature, and the differences between cleaning techniques and schedules effectiveness. Moreover, the study provides a review of statistical and artificial intelligence models used to predict PV performance and its prediction accuracies in terms of data size and complexity. Finally, the study draws attention to several research gaps that warrant further investigation. Among these gaps is the need for proper dynamic optimisation models for cleaning schedules and a more advanced machine and deep learning models to predict dust accumulation while considering environmental and ageing factors.

I. Introduction

Global population and economic growth have significantly increased the demand on electricity. According to (IEA 2011), electricity consumption rose from 10,116 TWh to 23,105 TWh over the last twenty years and is expected to increase by more than 50% by 2030 (IEA 2011), this exponential increase in demand adds burden to the existing conventional methods of generating electricity, which are neither reliable nor environmentally friendly with potential complete depletion (Al-Maamary, Kazem, and Chaichan 2017). As a result, the world has shifted the focus to clean and renewable energy resources in order to partially cover the electricity consumption and limit the dependency on depleted energy resources (Prakash and Bhat 2009). In particular, wind and solar electricity production are amongst the most utilised resources due to their effectiveness and simplicity compared with others (Tyagi et al. 2013).

Moreover, the remarkable reduction in the associated cost, as well as the ambitious policies for utilising renewable energy resources, has accelerated the installed capacity of solar and wind projects worldwide (Kazem 2011). It is expected that wind and solar total contribution from renewable energy resources in generating electricity will reach 31% in 2030 (Ellabban, Abu-Rub, and Blaabjerg 2014).

Despite solar energy popularity due to being abundant, clean, inconsumable, easy to install and maintain, and safe (Chu and Meisen 2011; Dincer 2000; Sarver, Al-Qaraghuli, and Kazmerski 2013; Comerio et al. 2021; Mekhilef, Sadur, and Safari 2011; Kalogirou 2013), it is vulnerable to different non-controllable weather conditions (Chaichan and Kazem 2016). There are two main solar panel types: Photovoltaic (PV), and Concentrated Solar Power (CSP). The PV panel converts direct sunlight into electricity, while CSP converts sunlight to heat, which is then used to generate electricity (Solar.Feed 2019). Hernández-Moro and Martínez-Duart conducted an analytical comparison between PV and CSP using the calculated levelized cost of electricity (LCOE) and the future evolution of the LCOE between 2010 and 2050 (Hernández-Moro and Martínez-Duart 2013). They recommended using PV technology on Earth areas with middle to high latitudes, while CSP technology in arid areas with low latitudes. The optimal solar irradiation is concentrated in the solar belt region, including North Africa and the Middle East, which are mostly desert areas (Mazumder et al. 2014). But the climate challenge in this region is the high levels of dust, pollution, and ambient temperature which are adversely affecting the performance and operation cost of PV systems (Kazem et al. 2020; Namdari et al. 2018).

Literature is rich in studies investigating the impact of design parameters, such as type of PV panel and tilt angle, and environmental factors, such as ambient temperature, solar radiation, wind speed, dust, and relative humidity on PV performance (Sharma and Chandel 2013; Ameur et al. 2020). These factors are correlated and jointly impact the operational characteristics of the PV system, such as the current and voltage which are the two main components of power.

The main purpose of this paper is to review the recent literature regarding the joint impact of dust accumulation along with other environmental factors on PV performance.
and dust accumulation prediction models, to identify potential research gaps that warrant further research.

Amongst all related topics to PV systems performance, this review sheds the light mainly on the impact of dust accumulation on the performance of PV panels as an influential factor. The review also analyses the impact of other meteorological, design, and operational factors on the performance of PV panels as well as their contribution to promoting dust accumulation. It also reviews the cleaning methods during the lifetime of PV systems operation; which would lead to enhanced optimisation models in terms of frequency and scheduling of cleaning. Finally, this review incorporates a section for predictive models of PV systems' efficiency that have been proposed recently. The purpose of this investigation is to critique the gaps and the limitations of the reviewed research which would serve as seeds for warranted future research.

Several review studies have discussed dust accumulation challenge from different perspectives and for different purposes. For example, Sarver et al. have reviewed research focused on the role of the PV panel surface type (transmissive and reflective) to mitigate soiling effect on the performance of PV panels (Sarver, Al-Qaraghuli, and Kazmerski 2013). Another stream of review papers focused on the significant impact of cleaning on the technical and economic aspects of PV systems (Kazem et al. 2020; Jaswal and Sinha 2021; He, Zhou, and Li 2011). Once again, the focus of these articles on the impact of chemicals and cleaning methods and not scheduling of cleaning cycles. The uniqueness of this paper is that it focuses on metallurgical and design parameters impact on different dust accumulation mechanisms.

This paper is organised as follows: section II outlines the proposed review methodology, section III explains the significance of studying dust accumulation and its impact on PV panels performance, section IV discussed the impact of dust particles and depositions on the performance of PV panels, section V clarifies the performance parameters of PV systems and investigates the impact of several factors on the performance of PV systems, section VI represents the preventive methods for dust accumulation during the design and development stage of PV panels, section VII summarises the cleaning methods and techniques, section VIII investigates the models used for forecasting the PV output power based on different factors, section IX recaps the extracted research gaps from the reviewed literature, and the paper concludes with section X highlights recommendations for future research.

II. Methodology

The review methodology is in accordance with Tranfield et al.’s guidelines for conducting a systematic review (Tranfield, Denyer, and Smart 2003) and depicted in Figure 1. The first stage is planning the review, it starts with conducting semi-structured interviews with four subject matter experts (SME). The first SME is a solar energy researcher and several patents holder while the second, third, and fourth are practitioners working for solar system manufacturing and installation companies. All three experts confirmed the need to tackle the dust accumulation issue and expressed interest in the review.

These recommendations have motivated the authors to identify the research problem, which is mainly about reviewing and studying the impact of dust accumulation along with other influencing environmental factors on PV systems performance. Also, a set of research questions have been stated to initiate the review, namely, what is the impact of dust accumulation on the PV panel performance? what is the impact of different environmental factors on the performance of PV panels? and what are the available PV panel energy prediction models? The last question includes methods used for developing models and variables included in the model.

The second stage is conducting the review, where recent studies are reviewed, based on the following keywords dust accumulation impact on PV; environmental impacts; weather conditions; soiling impact on PV; PV performance; PV cleaning: forecasting techniques; predicting techniques; artificial intelligence techniques; machine learning; and deep learning in peer-reviewed journals and research engines such as google scholar, IEEE, Scopus, and Science Direct. The inclusion criteria cover relevant, clear, recent, and high-quality studies to answer the proposed research questions.

Other aspects such as the pure technical studies that were focused on cleaning procedures and metallurgical processes to maximise the efficiency of PV panels were outside the scope of this study, yet they were mentioned briefly. The evaluation and screening of papers was mainly performed over several stages: initial screening based on the title and keywords, then screening based on the relevance of the abstract, and finally, through a thorough reading of the research paper.

The review covers the last 10 years only to assure recency of research. However, few key leading studies conducted before the coverage period were included due to its importance. The keywords search resulted initially in 18,841 articles. The screening process resulted in a total of 278 papers used for this review.

The third stage is disseminating the results including a comprehensive critique for the reviewed research papers and extract research gaps and recommendations for future work. The next sections provide a summary of the findings that will be used to attempt to answer the three research questions. The first part highlights the percentage of losses in performance parameters of different PV technologies due to soiling and dust accumulation in different countries. The second part investigates the performance of PV systems, the parameters that are considered to measure the performance including the operational and environmental. The third part provides a review of environmental forecasting models including artificial intelligence techniques and their accuracy. A critical review is presented after each section to highlight the potential challenges and opportunities that are worthy of future investigations.

III. Impact of dust accumulation on pv performance

The degradation in the performance due to soiling or dust accumulation affects the feasibility of PV systems drastically. Several studies have quantified the losses due to soiling or dust accumulation. Ilse et al. suggested that the financial losses due to dust accumulation were forecasted to be between 4% and 7% in 2023 (Song, Liu, and Yang 2021; Ilse et al. 2019b), which
signifies the need to understand and investigate performance losses due to dust accumulation.

The adverse impact of dust accumulation has been recognised and shifted the focus towards conducting cleaning activities to eliminate this environmental factor (Chiteka, Arora, and Sridhara 2020). Figure 2 illustrates the conducted researches per year between 1999 and 2022 respectively using Scopus (Scopus 2021). It is noticeable that there is an increasing interest in this field of research due to the associated performance and economic impacts.

Table 1 summarises the quantified soiling losses in several studies, while Figure 3 provides a graphical summary of losses by panel type in terms of duration. Based on the results, the following observations can be made:

- There is a significant difference in the reported losses based on the duration of the study, the location of the experiment, the PV technology used in the study, and the type of experiment.
Table 1. Quantified losses (in %) due to soiling or dust accumulation.

| Type | Country       | Ref.                                      | Perf. | Duration                  |
|------|---------------|-------------------------------------------|-------|---------------------------|
| c-Si | KSA           | (Adinoyi and Said 2013, Nimmo and Said 1981) | E     | 20–50                     |
| c-Si | Australia     | (Tanesab et al. 2018, Tanesab et al. 2015, Yap, Baig, and Halawa 2014) | P     | 4.5                       |
| c-Si | Indonesia     | (Tanesab et al. 2018)                     | E     | 22                        |
| c-Si | Chile         | (Fuenteleba et al. 2015, Ferrada et al. 2015, Urrejola et al. 2016) | P     | 8                         |
| TF & c-Si | India       | (Bergin et al. 2017, Bhaiker and Arya 2015, Rao et al. 2014) | E     | NA                        |
| c-Si | Jordan        | (Essalaimeh, Al-Salaymeh, and Abdullah 2013, Saluos 2015) | E     | 31–35                     |
| c-Si | Pakistan      | (Bashir et al. 2014, Ullah et al. 2020)   | P     | 16–20                     |
| c-Si | NA            | (Comerio et al. 2021, Sulaiman et al. 2014, Zaitidee et al. 2016, Rouway et al. 2020, Jiang, Lu, and Sun 2011) | E     | 85                        |
| c-Si | Senegal       | (Ndaiye et al. 2013)                      | P     | 54                        |
| CSP  | San Diego     | (Mejia, Kleissl, and Bosch 2014)          | E     | 0.21                      |
| TF & c-Si | Thailand    | (Ketjoy and Konyu 2014)                   | E     | 5.79–7.28                 |
| TF & c-Si | Qatar        | (Guo et al. 2015, Touati, Al-Hitmi, and Bouchech 2012) | E     | 10                        |
| TF   | Egypt         | (ElDin et al. 2013)                      | E     | 9.86                      |
| TF   | USA           | (Caron and Littmann 2012)                | E     | 11.5                      |
| c-Si | Belgium       | (Appels et al. 2013)                    | E     | 4                         |
| c-Si | UAE           | (Al-Sabounchi, Yalyali, and Al-Thani 2013, Hachicha, Al-Sawafaa, and Said 2019) | P     | 12.7                      |
| c-Si | Iraq          | (Al-Amrri, Ghazi, and Mustafa 2013, Saidan et al. 2016) | P     | 26                        |
| c-Si | Spain         | (Zorilla-Casanova et al. 2011)           | E     | >20                       |
| c-Si | Malaysia      | (Sulaiman et al. 2011)                  | E     | 50                        |
| c-Si | Oman          | (Touati, Al-Hitmi, and Bouchech 2012)    | P     | 38.1                      |
| c-Si | Poland        | (Klugmann-Radziemska 2015)               | E     | 25.5                      |

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The majority of research was conducted for a period less than a year (Comerio et al. 2021; Adinoyi and Said 2013; Nimmo and Said 1981; Bergin et al. 2017; Essalameh, Al-Salaymeh, and Abdullat 2013; Bashir et al. 2014; Mejia, Kleissl, and Bosch 2014; Ketjoy and Konyu 2014; Guo et al. 2015; ELDin et al. 2013; Caron and Littmann 2012; Appels et al. 2013; Al-Sabounchi, Yalyali, and Al-Thani 2013; Hachicha, Al-Sawaf, and Said 2019; Al-Ammri, Ghazi, and Mustafa 2013; Saidan et al. 2016; Al Siyabi et al. 2021). The findings from these studies suggest that dust accumulation has a strong impact on performance that may reach 40% in some cases. However, these studies did not consider all weather changes during different seasons over a whole year. More accurate and generalised results can be obtained over a longer period of time that cover all variations of weather conditions.

Some studies have drawn conclusions regarding the performance losses due to dust accumulation with no clear specification of the period of study (Bhasker and Arya 2015; Rao et al. 2014; Saluos 2015; Sulaiman et al. 2014; Zaihidee et al. 2016; Jiang, Lu, and Sun 2011; Rouway et al. 2020; Sulaiman et al. 2011); which may result in misleading conclusions.

Losses vary even within the same country. Such differences may be attributed to different time periods, different experimental settings (indoor, outdoor, or simulation, soiling type), and different PV technologies. For example, Ullah et al. suggested 10% loss for low soiling and 40% for heavy soiling (Ullah et al. 2020).

Data suggest conflicting results when comparing the performance losses for monocrystalline panels and polycrystalline panels. Some studies such as the one conducted in Pakistan for 3 months (Bashir et al. 2014), and the one in Senegal (Ndiaye et al. 2013), suggest that mono has higher losses than polycrystalline. However, a study conducted in Thailand over a 5 month period showed opposite results (Ketjoy and Konyu 2014). Similarly, it suggests that the losses in the thin film are higher than crystalline panels (both monocrystalline and polycrystalline) for a 5 months period of study (Ketjoy and Konyu 2014). The opposite results were suggested (Touati, Al-Hitmi, and Bouchech 2012), which was conducted for 100 days. Such conflict in findings may raise the need for a well-designed comparison environment for different technology types under similar conditions with validation experiments to have more conclusive results. Hence, more conclusive studies with the objective of comparing different technologies performance under the same conditions are warranted. Additionally, these different results for the reported soiling losses for different PV technologies are illustrated in Figure 3, where it can be
noticed that for the same duration of study and the same PV technology, soiling losses can differ based on the location and the impact of other environmental, design, and structural factors, this can be clearly observed for the crystalline panels over a period of 1, 1.25, 3.3 and 6 months. Also, for different technologies, the reported soiling losses would not necessarily increase if the duration of exposure to dust increases. This result is valid for both mono and poly crystalline panels over a period of 3 and 5 months and might be justified by the impact of other influencing factors.

- The indoor experiments presented in (Saidan et al. 2016; Bhasker and Arya 2015; Saluos 2015; Sulaiman et al. 2014) showed different soiling losses. The purpose of these studies was to evaluate the effect of different dust particles or sizes and predict the required cleaning cycles. However, the indoor studies lacked the actual and different combination of physical and chemical characteristics of dust and its stochastic nature over different times of the year. Majority of these experimental studies uses ‘one factor at a time’ testing strategy which does not reflect the interaction effect between different environmental and design factors. There is a need to conduct further studies to correlate indoor testing and external environment. A standard indoor testing method that is agreed upon would be ideal to make comparisons between different studies more applicable.

### IV. Impact of Dust Particles and Depositions on the performance of pv systems

Characteristics of dust particles and depositions have a significant impact on the performance of PV panels. In this regard, Kazem et al. have provided a comprehensive review of the dust characteristics of six dust pollutants and cleaning methodologies impact on the technical and economic aspects of cleaning (Kalogirou 2013). Likewise, dust particle mechanisms and characteristics including deposition and rebound were reviewed to understand the behaviour of soiling and propose design mitigation methods for PV panels (Song, Liu, and Yang 2021; Figgis et al. 2017; Zhao et al. 2021; Jamil et al. 2017).

Additionally, Menoufi proposed a performance indicator that is calculated for each location considering the dust deposition rate and the average dust density (Menoufi 2017). The proposed indicator is called photovoltaic soiling index (PVSIs), and it is suggested to be listed in the datasheet of PV panels. However, this index is still not applied in mass production plants.

Particulate matters (PM) are known as the major pollutants in industrial areas due to vehicles and chimneys emissions and it contributes to the negative impact on the performance of PV panels either by the direct accumulation on PV panels, or by the indirect effect through settling in the atmosphere prohibiting the effective absorption of solar irradiance by PV panels (Kazem and Chaichan 2019; Boyle, Flinchpaugh, and Hannigan 2016; Li, Mauzerall, and Bergin 2020; Benghanem et al. 2018). Moreover, Saluos investigated PV panels operational characteristics including Voc, Isc, and Power as a function of dust depositions (Saluos 2015). The same investigation showed that the power losses may reach up to 90% based on the characteristic of dust. Likewise, Sulaiman et al. examined several kinds of depositions (dust, water, sand, and moss) and reported a performance loss of 85% due to the exposure of different dirt depositions (Sulaiman et al. 2014).

Understanding the impact of dust depositions on PV panels and how to mitigate them requires special attention especially in the design and development stages of PV panels, yet it would be an opportunity to study the feasibility and applicability of applying anti-reflective and self-cleaning methods on the currently installed PV systems, also, it would lead to the application of most effective cleaning methods based on the dominant dust depositions. This would contribute to enhancing the economic and operational status of PV systems; the cleaning schedules would be adjusted, the required maintenance would be optimised, and the overall yield would be improved.

### v. Impact of environmental factors on the performance of pv systems

The performance and efficiency of PV systems depend on the stochastic outdoor environmental factors (Singh, Sulaiman, and Singh 2013; Gholami, Saboonchi, and Alemrajabi 2017; Al-Shahri et al. 2021). The prolonged exposure of PV panels to the outdoor conditions increases their degradation rate (Corkish et al. 2013; Kumar and Kumar 2017). Table 2 summarises relevant survey studies conducted. Based on the summary, the following points were highlighted:

- Very few studies have comprehensively and simultaneously considered all environmental factors which include ambient temperature (T), solar irradiance (Si), humidity (H), wind speed (Ws), and dust accumulation (D) (Al Siyabi et al. 2021; Kazem and Chaichan 2016). Several studies have confirmed the significant impact of Ws and H for some locations (Al Siyabi et al. 2021; Zorrilla-Casanova et al. 2011; Yoo 2011; Sonsuz et al. 2020; Beattie et al. 2012; Csavina et al. 2014; Goossens et al. 2019; Elminir et al. 2006; Mekhilef, Saidur, and Kamalizarvestani 2012), yet both factors were not included in the majority of studies. More comprehensive studies focused on modelling losses as a function of all of these environmental factors for specific designs are warranted.

- More than 50% of the reviewed studies overlooked the impact of the design factors: tilt angle (At) and azimuth angle (Az); which have a significant impact on the efficiency of PV panels. At and Az control the amount of irradiance absorbed by the panel and the orientation of panels with respect to the sun which affects the angle of incidence (AOI). Therefore, it is important to consider them as well when assessing the performance of the PV system.

- Amongst all performance measures, power is the most widely used measure due to ease of measurement at the panel or inverter scale. Power depends on the Isc and Voc
Table 2. Reviewed studies on the performance of PV panels under different environmental and design conditions.²

| Ref. | Environmental factors | Design factors | Performance Measures | Experimental Type | Period |
|------|-----------------------|----------------|----------------------|-------------------|--------|
| (Amur et al. 2020) | X X X | X | X | X | X | 1 week |
| (Ham et al. 2011) | X X X | X | X | X | X | 1 year |
| (Demain, Journée, and Bertrand 2013) | X X X | X | X | X | X | 8 months |
| (Jin et al. 2017) | X X X | X | X | X | X | 1 year |
| (Li 2013) | X X X | X | X | X | NA |
| (Mansour et al. 2021) | X X X | X | X | X | 1 year |
| (Cai et al., Carretero, and Sidrach-de-Cardona 2014) | X X X | X | X | X | 1 year |
| (Eke and Dericman 2013) | X X X | X | X | X | 1 year |
| (Marion, Deceglie, and Silverman 2014) | X X X | X | X | X | 1 year |
| (Micheli et al. 2014) | X X X | X | X | X | 1 year |
| (Berg et al. 2017) | X X X | X | X | X | 6 months |
| (Tanes et al. 2015) | X X X | X | X | X | 18 years |
| (Sulaiman et al. 2011) | X X X | X | X | X | 1 year |
| (Fuentelba et al. 2015) | X X X | X | X | X | 21 months |
| (Hachicha, Al-Sawaf, and Said 2019) | X X X | X | X | X | 5 months |
| (Cemero et al. 2021) | X X X | X | X | X | Days |
| (Sulaiman et al. 2011) | X X X | X | X | X | NA |
| (Kazem and Chichan 2016) | X X X | X | X | X | NA |
| (Al Siyabri et al. 2021) | X X X | X | X | X | 5 weeks |
| (Guo et al. 2015) | X X X | X | X | X | 6 months |
| (Suz et al. 2020) | X X X | X | X | X | 210 days |
| (Rao et al. 2014) | X X X | X | X | X | NA |
| (Saidan et al. 2016) | X X X | X | X | X | 1 day-1 month |
| (Tanes et al. 2018) | X X X | X | X | X | 1 year |
| (Jiang, Lu, and Sun 2011) | X X X | X | X | X | NA |

which are always available on the monitoring system or the inverters’ display. Nevertheless, the readings for the power do not give a full indication regarding the current compared to the expected performance. Instead, performance ratio (PR), which represents the ratio of the actual power to the expected or theoretical power, is a more realistic performance metric.

- Although it is recommended to validate simulation or indoor experiments with validation results were not provided in most of the studies. Few studies conducted more than one type of experiment for evaluating the performance or for validation purposes (Hachicha, Al-Sawaf, and Said 2019; Al Siyabri et al. 2021; Rao et al. 2014; Yoo 2011; Mahdi et al. 2017; Mani and Pillai 2010; Manokar et al. 2018).

More details on the impact of environmental factors on the performance of PV panels are provided in the next subsections.

### Impact of ambient temperature

To reduce the impact of high temperature, photovoltaic/thermal (PV/T) systems were introduced (Al-Waeli et al. 2017b, 2017a). These systems use phase-changing materials with nanofluids to decrease the temperature of PV panels and use stored heat for other applications (Al-Waeli et al. 2018). However, implementing such technology requires major panel design changes.

Ambient temperature has a higher negative impact on the thin film panels’ (TFP) efficiency compared to crystalline panels (CRP) (Touati, Al-Hitmi, and Bouchech 2012). Al Siyabri et al. suggested that the efficiency of crystalline cells reduces by 0.248% for each one degree Celsius increase (Al Siyabri et al. 2019). Artificial exposure to high temperatures has resulted in a power reduction that reached 20.22% for crystalline panels (Kazem and Chichan 2016). The increased temperature results in a slight increase in Isc and a significant decrease in Voc and accordingly a reduction in the output power (Majid et al. 2014; Cherder et al. 2015; Nair, Jose, and Ravindran 2016). Several studies confirmed reduction in PV performance in different locations such as Saudi Arabia (Adinoyi and Said 2013; Mansour, Khan, and Al-Sulaiman 2021), Italy (Micheli et al. 2014), Spain (Cañete, Carretero, and Sidrach-de-Cardona 2014), and US (Marion, Deceglie, and Silverman 2014). In terms of dust presence, higher ambient temperature has a direct negative impact on panels and an increase in the soiling losses (Al-Sabounchi, Yalyali, and Al-Thani 2013; Fuentelba et al. 2015).

### Impact of solar irradiance

Similarly, the performance of PV systems is highly dependent on the amount of irradiance hitting the front side of the PV panel (Amur et al. 2020; Kazem and Chichan 2016; Micheli et al. 2014; Marion, Deceglie, and Silverman 2014; Sharma and Chandel 2013; Eke and Demirman 2013). PV panels are at their best operating status when the irradiance is at its maximum and the ambient temperature is at its minimum (Mohanty and Kale 2021). This refers to the ability of more photons to be absorbed by the PV panel and move the electrons to generate current. The increase in Isc is noticeably higher than the increase in Voc and the overall output power will increase accordingly.

Several studies suggested that irradiance is the most influential factor compared to others (Cañete, Carretero, and
Sidrach-de-Cardona 2014; Kaldellis and Kokala 2010). This is supported by a study conducted in Korea for building integrated photovoltaic project (BIPV) (Yoo 2011), where the results showed that higher output power measurements are associated with higher solar irradiance levels. Yet, dust and dirt can cause a remarkable reduction in the efficiency of PV panels up to 15% for BIPV (Kaldellis and Kokala 2010). To the authors’ best knowledge, there are few studies attempted at measuring losses due to dust as a function of irradiance. Modelling dust losses as a function of irradiance can improve cleaning effectiveness.

Impact of humidity

Humidity also has a negative impact on the performance of PV panels. When humidity increases, moisture will turn dust into mud (Al Siyabi et al. 2021) and accelerate adhesion of dust layer to PV panels’ surfaces (Zorrilla-Casanova et al. 2011; Beattie et al. 2012), which require special and frequent cleaning (Adinoyi and Said 2013; Mahdi et al. 2017; Kazem and Chaichan 2019). Cleaning becomes more challenging in desert areas due to water scarcity (Al-Sabounchi, Yalyali, and Al-Thami 2013). Kazem and Chaichan studied the impact of humidity on PV panels experimentally and claimed that humidity could reduce PV power output by 32.24% (Kazem and Chaichan 2016). Touati et al. compared TFP and CRP and found that the effect of humidity is higher on the former (Touati, Al-Hitmi, and Bouchech 2012). Furthermore, if humidity penetrates the PV cell through the edges, it would cause corrosion (Kempe 2005), which results in a reduction in the adhesion between the cell and the frame, and consequently additional deterioration due to increased current leakage (Munoz et al. 2011).

Impact of Wind Speed

Wind speed and its direction contribute significantly to the efficiency of PV systems (Csavina et al. 2014), and amount of dust accumulation (Goossens et al. 2019; Elminir et al. 2006). Low wind speed tends to stimulate dust accumulation (Mehkilef, Saidur, and Kamalisarvestani 2012), while high wind speed would dispel dust accumulation and positively contribute to the natural cleaning of PV panels (Mani and Pillai 2010). The success of natural cleaning depends on the orientation of the installed panels, wind direction and speed, and the source and type of dust (Mehkilef, Saidur, and Kamalisarvestani 2012; Hee et al. 2012).

An additional positive effect of wind speed is the cooling effect it has on the PV panel which increases the absorbed irradiance due to blowing the accumulated dust away (Kazem and Chaichan 2016; Sonsuz et al. 2020), and decreasing the humidity (Sonsuz et al. 2020). A predictive model for output power based on recorded data for wind speed and panel’s temperature for 1 year was developed using an artificial neural network (ANN) for a PV plant in India (Mohanty and Kale 2021), while holding irradiance constant. Similarly, another model was developed to study the effect of wind speed on output power while holding irradiance and ambient temperature constant (Manokar et al. 2018). The latter model suggested that output power increases with wind speed up to a certain speed (Manokar et al. 2018). Another study suggested that output power increases with the increase in irradiance and decreases with the increase in ambient temperature, humidity, and wind speed (Garg 2017). Such models highlight the interaction effects that exist among the environmental factors and the need for including all of them to get an accurate prediction of the power.

Impact of dust accumulation

Dust is one of the important factors that are affecting the efficiency, performance, and profitability of PV systems (Kazem et al. 2020; Bergin et al. 2017; Smestad et al. 2020). Soiling losses are attributed to soil, dust, dirt, vehicle and power plant smoke, fog, particulate matters, ocean spray, and any other material that covers the PV panel and increases sun light scatter and decreases absorption (Guo et al. 2015; Conceição et al. 2019; Kazem, Chaichan, and Kazem 2014; Kinney 2018; Li et al. 2018), resulting in PV performance losses (Kazem and Chaichan 2016; Mahdi et al. 2017; Muñoz-García, Foursis, and Pilat 2021).

Dust losses have been widely investigated (Al Siyabi et al. 2021) and were proven to be higher than the losses due to ambient temperature or relative humidity (Touati, Al-Hitmi, and Bouchech 2012). However, PV panels dust accumulation causes increase in panels’ temperature which will lead to a drop in the output power (Li 2013; Wilson et al. 2016). Dust particles may accumulate on PV panels due to natural causes or anthropogenic activities (Kaldellis and Kapsali 2011; Bodenheimer, Lensky, and Dayan 2019), such as vehicles, construction, sandstorm, pollution, airborne particles, bird dropping, etc. (Sharma and Chandel 2016; Park et al. 2011; Rieger et al. 2017; Kazmerski et al. 2016). In this regard, Ghazi et al. realised that high populated regions in the Middle East and North Africa have higher levels of dust accumulation compared to other regions in the world (Ghazi, Sayigh, and Ip 2014; Maghami et al. 2016).

There are several factors that affect the accumulation of dust on PV panels (Sonsuz et al. 2020; Mani and Pillai 2010), such as the local environment (Hosseini, Kermani, and Arabhosseini 2019; Rashki, Kaskaoutis, and Sepehr 2018), dust properties (Sulaiman et al. 2011; Zhao et al. 2021; Klugmann-Radziemska 2015; Ahmed, Kazem, and Sopian 2013; Darwish et al. 2015; Tanesab et al. 2019; Benatallah et al. 2012; Molki 2010; Kumar and Chaurasia 2014; Darwish et al. 2018; El-Shobokshy and Hussein 1993; Kaldellis, Fragos, and Kapsali 2011; Javed et al. 2017; Micheli and Muller 2017; Ilse et al. 2018; Sun et al. 2018), PV panels surface type and use of anti-soiling glass or coating (Jiang, Lu, and Sun 2011; Goossens 2018; Pliougine et al. 2013; Ilse et al. 2019a; Said and Walwil 2014), and tilt angle (Hachicha, Al-Sawafita, and Said 2019; Sharma et al. 2013). The local environment includes location, human activities, climate conditions and type of vegetation while dust properties include size, weight, density, and particles morphology. Dust losses are usually measured by comparing the output power of a clean panel and a dusty panel under the same installation and environmental conditions. A soiling ratio parameter (PR) of the maximum output
power Pmax or the short circuit current Isc of soiled or dusted panel to a clean one is a common metric (Tanaseb et al. 2015; Micheli et al. 2017; Vázquez and Rey-Stolle 2008; Gholami et al. 2018; Nepal et al. 2018). Dust losses are highly affected by high ambient temperatures (Al-Sabounchi, Yalyali, and Al-Thani 2013). In arid and semi-arid regions, the reduction in output power due to dust accumulation can reach up to 50% (Mallineni et al. 2014). Researchers reported different losses for different locations, durations, and combinations with other environmental factors. For example, Charabi and Gastli reported a soiling ratio up to 81% due to the integrated impact of high ambient temperature and dust accumulation in Oman (Charabi and Gastli 2013).

Similarly, Al Siyabi et al. reported that a soiling loss of 7.5% and 12.5% can result in a monthly generation reduction of 5.6% and 10.8% respectively of a 2MWp car park in Oman (Al Siyabi et al. 2021). Comparable hot weather conditions are dominant in Baghdad-Iraq, where it was noticed that the output power of the crystalline solar panels was decreased by more than 60% for 3 months due to dust accumulation (Al-Ammri, Ghazi, and Mustafa 2013). In Saudi Arabia, Adinoyi and Said have shown that the reduction in power due to dust accumulation on crystalline panels was 50% for a period of 6 months (Adinoyi and Said 2013). Also, the uniformity of dust distribution on PV panels increases the losses in performance due to dust accumulation (Bergin et al. 2017; Michelsm et al. 2015).

The performance of two PV technologies (TPF and CRP) was compared under the effect of dust accumulation and ambient temperature for 21 months in Chile (Fuentenalba et al. 2015). It was found that the PR is reduced by 3.7–4.2% for TPF with the decrease in temperature while it is reduced by 4.4–4.8% with the increase in temperature. For CRP, the impact is more apparent where the PR is reduced by 1.8–2.4% when the temperature decreases and 3.7–6.2% when the temperature increases. Another study in Chile was conducted in a heavily polluted area for 2 years.

Urrejola et al. reported a degradation in the performance of polycrystalline panels of 1.29%, monocrystalline panels of 1.74%, and thin film of 2.77% (Urrejola et al. 2016). These results contradict the findings of another study in Qatar (Touati, Al-Hitmi, and Bouchech 2012), and California (Nimmo and Said 1981), where TFP had better efficiency than CRP when exposed to dust in desert areas. A similar study was conducted in Chile and showed the same conclusion when the energy yield and PR of different crystalline silicon panels were compared during summer and winter (Ferrada et al. 2015). Bashir et al. has compared the performance of different CRP (mono and poly) for 3 months during winter where the loss in power was higher in monocrystalline panels (Bashir et al. 2014).

Mejia et al. monitored the efficiency of CSP station during a dry period in summer and reported a drop of 0.21% per day (Mejia, Kleissl, and Bosch 2014). The same study suggested that the drop in efficiency can be restored by a rainfall event. Several studies showed that dust accumulation impacts output power and current of different types of CRP while the voltage is not impacted since dust impacts the amount of irradiation that is absorbed by the panel (Rao et al. 2014; Ndiaye et al. 2013; Al-Hasan and Ghoneim 2005). Unlike Middle Eastern countries, a case study in Belgium has shown that the impact of soiling losses were 3% and 4% during a rainfall 5-week outdoor experiment using the optimal tilt angle (Appels et al. 2013). The loss in the efficiency of TFP reached 9.86% for a 30-days outdoor experiment in Egypt, where it was confirmed that Isc and power are mainly affected by dust accumulation.

Many controlled indoor experiments have been conducted to study the effect of dust accumulation on PV panel performance without considering other weather conditions (Jiang, Lu, and Sun 2011; Al Shehri et al. 2017). For example, Sulaiman et al. conducted an indoor experiment by exposing PV panels to artificial dust particles and a constant source of light and reported an efficiency loss of 50% (Sulaiman et al. 2011). Similar studies conducted using natural dust reported an efficiency loss of 35% per month (Bhasker and Arya 2015), while using an artificial one showed a significant efficiency decrease using mud and talcum as mud (Rahman et al. 2012).

In the UAE, Hachicha et al. has conducted an indoor and outdoor experiment using dust collected on the roof of a building. Results suggest a linear relationship between the density of dust and the normalised power with a slope of −1.7% per g/m² (Hachicha, Al-Sawafta, and Said 2019). A similar outdoor experiment showed a loss of 12.7% in power during the period of study in Kuwait (5 months) with a similar linear relationship by where the power was dropped by 34% for each g/m² (Al-Hasan and Ghoneim 2005). Several other studies confirmed the linear relationship between dust density and transmittance losses (Piedra, Llanza, and Moosmüller 2018; Pedersen, Strauss, and Selj 2016; Boyle, Flinchpaugh, and Hannigan 2015).

Additionally, Muñoz-Garcia et al. performed an indoor experiment to analyse the impact of dust accumulation by stimulating the weather of desert and the optical transmittance losses. Results showed power losses ranging from 4.73% to 6.90% and a dependency on the dust density (g/m²) and the condition in which it was accumulated (Muñoz-Garcia, Fouris, and Pilat 2021).

In addition to performance losses, dust accumulation may cause other damages to PV panels. Examples are surface damage due to sand erosion and permeability reduction which will contribute to additional deterioration in the performance of PV panels (Tagawa 2012).

Numerous researchers have compared different PV types to evaluate their performance and feasibility. For instance, Ameur et al. compared polycrystalline-Si, monocrystalline-Si, and amorphous-Si under real weather conditions for a period of 5 years in Morocco (Ameur et al. 2020). The results showed that polycrystalline-Si has better performance measures as well as lower LCOE value (0.10 USC/kWh) when compared to monocrystalline-Si and amorphous-Si. Similarly, Akhmad et al. suggested that thin film PV technology performs better than crystalline PV silicon in the tropical regions based on an outdoor study conducted for 2 years (Akhmad et al. 1997).

Likewise, Sasitharanuwat et al. compared the efficiency of thin film, polycrystalline, and hybrid solar panels for 6 months of operation in Thailand and concluded that the efficiency of thin film panels is the highest (Sasitharanuwat et al. 2007). Thin film panels have lower temperature coefficients than crystalline silicon panels (Kumar and Kumar 2017), but thin
VI. Preventive methods for dust accumulation

Preventive methods include the use of special anti-soiling coating materials of the PV surface (Sarver, Al-Qarahguli, and Kazmerski 2013; Jamil et al. 2017; Sayyah, Horenstein, and Mazumder 2014; Son et al. 2012). A significant increase in the density of short circuit current by 3.1% was achieved through applying a self-cleaning cover made of micro-structured fluorinated ethylene propylene (FEP) on the front surface of PV panels (Roshizar et al. 2020). The additional cover has self-cleaning properties and can decrease the irradiance reflection losses. Another technique was presented to characterise the evolution of the coating layer chemistry using small-angle X-ray scattering (SAXS), X-ray photoelectron spectroscopy (XPS), and X-ray absorption spectroscopy (XAS) which showed its effectiveness for the anti-soiling-coating material for PV panels (Moffitt et al. 2019).

In the context of angle of incidence (AOI), the increase in AOI will increase the reflectance of irradiance and reduce PV panel efficiency (Rajasekar, Boppana, and Tamizhmani 2015). Therefore, anti-reflective coating for PV panels is considered more resilient towards the effect of AOI (John 2015). Likewise, a recent review paper has shown that MgF₂, SiO₂, TiO₂, ZrO₂, and Si₃N₄ are the most used materials for anti-reflective coatings for the glass of PV panels, while manufacturing superhydrophobic surface for the glass layer of PV panels features the most effective method in self-cleaning (Sarkin, Ekren, and Sağlam 2020; Wu et al. 2022).

Furthermore, installation settings, such as tilt angle and orientation, control the amount of solar irradiance falling on the PV panel (Elminir et al. 2006; Demain, Journée, and Bertrand 2013; El-Sebai et al. 2010). The azimuth angle represents the orientation, which is the angle of east-west orientation in degrees. The zero value of the azimuth angle is when the PV panels stand facing the equator in Earth’s southern and northern hemispheres. Panels, in general, should face the south for the northern hemisphere and the north for the southern hemisphere, while the tilt angle depends on the daily, monthly and yearly path of the sun (John 2015; Yadav and Chandel 2013). This implies the need to optimise it for each site to increase the performance of solar panels (Micheli et al. 2014; Jin et al. 2017). The tilt angle has a vital role in maximising the solar irradiance that reaches the PV panel (Eke and Demircan 2013; Conceição et al. 2019; Lu and Hajimirza 2017; Xu et al. 2017).

Yadav and Chandel conducted a comprehensive review to study several optimisation techniques to determine the optimal tilt angle (Yadav and Chandel 2013). Moreover, a case study for maximising the output power based on optimising the tilt angle along with ambient temperature in five different cities in Saudi Arabia was presented in (Mansour, Khan, and Alsulaaiman 2021). Similarly, an experimental study was conducted by Ulah et al. to determine the optimal tilt angle for PV panels in Pakistan using radiation data from Energy Sector Management Assistance Programme (ESMAP) and National Renewable Energy Laboratory (NREL) (Ulah et al. 2020). The same study suggested energy losses of 13.5% and 26.2% for vertical and horizontal installation, respectively. In general, as the tilt angle increases, the dust accumulation on PV panels decreases due to gravitational effect on dust particles (Mekhilef, Saïdur, and Kamalasarvestani 2012).

Moreover, tilt angle affects the angle of incidence (AOI) which impacts performance losses (Marion, Deceglie, and Silverman 2014; Zhang et al. 2016). Based on these studies, the tilt angle and orientation of PV panels are site-dependent and their optimal values are determined for each site specifically (Sharma and Chandel 2013).

In addition, the structural design of PV panels can affect the accumulation of dust and the potential degradation in performance, it was found that frameless PV panels experience uniform distribution of dust, while the distribution of dust in the framed ones is nonuniform due to the increased accumulation at the bottom of the panel where the frame prohibits the flow of dust particle due to gravity (Javed et al. 2017; Sadat et al. 2021; Gostein et al. 2013). The frequent nonuniform distribution of dust leads to hotspots in PV panels which has a severe negative impact on the performance (AlDowsari et al. 2014).

VII. Cleaning

PV panels cleaning is a reactive method to enhance the performance of PV panels, it is considered as a significant maintenance cost (Jones et al. 2016), which should be performed when it is economically feasible (Faifer, Lazzaroni, and Toscani 2014; Cristaldi et al. 2012). PV plants usually have prescheduled cleaning cycles based on the forecasted soil losses in their locations. Cleaning the PV panels can be manual, or automatic (full or semi).

Cleaning can be wet or dry based on many conditions such as the severity of the accumulated dust and the type of dust. Manual cleaning is usually recommended for small-scale PV systems (Maghami et al. 2016; Sayyah, Horenstein, and Mazumder 2014) and is labour-intensive and costly if the water is scarce or unavailable at site (Kazem et al. 2020; Bergin et al. 2017). It is also recommended to use a good quality brush when conducting manual cleaning to avoid any adverse impact of the surface of PV panels (Al Shehri et al. 2016).

Automatic cleaning is recommended for medium-large scale PV systems as they are faster and more efficient (Sarver,
Al-Qaraghli, and Kazmerski 2013; Al Siyabi et al. 2021; Maghami et al. 2016). The automatic cleaning techniques include robots, drones, automatic brushes, etc. (Al-Housani, Bicer, and Koç 2019). Although automatic cleaning may reduce the water and manual operating costs, excessive use may affect the lifespan of PV panels and add additional cost component for replacing the defected panels (Supe et al. 2020).

Other recent cleaning methods include:

- Air flow from conditioning units (Assi et al. 2012).
- natural rain: a cheap and effective method with the challenge of controlling amount (Tanesab et al. 2016). Moreover, the tilt angle of PV panels should be greater than zero (García et al. 2011); otherwise, a layer of clay or mud will be formed on the PV panels (Kazem et al. 2020).
- Mechanical cleaning: using robots or engines to operate cleaning brushes with an option to be attached to water tank (Anderson et al. 2010).
- Electro-dynamic display (Mazumder et al. 2017): an expensive and fast method that can remove up to 90% of the dust within 2 min (Kazem et al. 2020). However, it depends on converting the dust to a dynamic state by using a high voltage source to generate electricity and charge the accumulated dust which by itself consumes energy. This method is more useful in arid regions (Mazumder et al. 2011).

The selection of a cleaning method depends on cost, location, system size, design features, and meteorological data (Kazem et al. 2020). Several studies have been conducted to monitor the soiling phenomenon on PV panels in order to plan for the cleaning activities. For instance, Google Earth Engine (GEE) is one of the methods that provides a cost-efficient and near real time monitoring for PV soiling losses (Supe et al. 2020). The majority of these methods have a fixed schedule even though environmental factors such as dust and rain are highly stochastic. Investigating a more flexible method with dynamic scheduling driven by accurate prediction models is promising.

**VIII. Output power forecasting/predicting models**

Forecasting operational or environmental factors for PV systems using artificial intelligent techniques is another area of research that drew the attention of many researchers in the last few decades. Figure 4 depicts a summary of machine learning (ML) and deep learning (DL) techniques used for forecasting while Table 3 provides a summary of prediction models studies surveyed.

**Figure 4 Alt Text:** A pie chart that demonstrates the percentage of using forecasting techniques to forecast solar performance and environmental indicators, neural network (45%), regression (24%), support vector machine (14%), decision tree (8%), extreme learning machine (4%), and rainforest (4%).

Neural network techniques were employed in predicting performance and environmental factors in PV systems. ANN is the most applied technique and resulted in the best accurate predictive models compared to other neural network tools with the exception of one study conducted in KSA where multilayer perceptron (MLP) resulted in best predicting accuracy compared to DT, KNN, and SVM.

Regression tools were also used to forecast the performance and environmental factors in PV systems. The most frequently used was linear regression (LR). However, other prediction techniques such as non-linear regression (NLR) (Omar Nour-eddine et al. 2021; Louazni et al. 2020), support vector machine (SVM) (Bandong et al. 2019), extreme learning machine (ELM) (Al-Kouz et al. 2019), artificial neural network (ANN) (Javed, Guo, and Figgis 2017), multilayer perceptron (Pulipaka, Mani, and Kumar 2016), and decision trees (DT) have outperformed LR (Touati et al. 2017). Furthermore, an NLR model resulted in higher prediction accuracy than ANN for the power based on ambient temperature and irradiance as inputs (Louazni et al. 2020). Similarly, random forest (RF) outperformed logistic regression (Log) in one study with the objective of forecasting soiling losses as a function of temperature and solar irradiance (Heinrich et al. 2020). Gaussian Process regression (GP) was used twice: first for predicting power as a function of temperature, irradiance, and wind speed and showed better performance than DT (Hossain et al. 2017). In contrast, the second study showed that the performance of DT in predicting soiling losses was better than GP considering temperature, irradiance, and dust accumulation as inputs (Shaaban et al. 2020). Such conflicting results may be due to the type, sample size, amount, and complexity of data and model characteristics.

In some cases, additional sophisticated methods were applied using metaheuristic techniques to increase the prediction accuracy such as Artificial Bee Colony Support Vector Machine (ABC-SVM) for power prediction using irradiance, temperature, humidity, and wind speed as inputs, when compared to the original SMV technique (Mo et al. 2018), and Particle Swarm Optimisation and Extreme Learning Machine (PSO-ELM) for irradiance prediction using irradiance, temperature, and humidity, when compared to DT, SVM, ELM, and GRNN (Feng et al. 2020).

The nature and size of input and output data influence the selection of the prediction technique. For example, regression
## Table 3. Reviewed prediction studies analysis.

| Ref.                         | Output | Type        | Design | Weather/ Environmental | Operational | Experimental Type |
|------------------------------|--------|-------------|--------|-------------------------|-------------|-------------------|
| (Ziane et al. 2021)          | P      | poly-Si     | A_T    | A_A                     |             | Out               |
| (Graditi, Ferlito, and Adinoff 2016) | P      | poly-Si & a-Si | A_T    | A_A                     |             | Out               |
| (Ahmad, Moushesh, and Rezgui 2018) | P      | NA          | A_T    | A_A                     |             | Out               |
| (Bouchoucha et al. 2020)     | P      | poly-Si     | A_T    | A_A                     |             | Out               |
| (Omar Nour-eddine et al. 2021) | P      | poly, mono, a-Si | A_T    | A_A                     |             | Out               |
| (Louzani et al. 2020)        | P      | mono-Si     | A_T    | A_A                     |             | Out               |
| (Rana, Koprinska, and Ageidias 2016) | P      | NA          | A_T    | A_A                     |             | Out               |
| (Touati et al. 2017)         | P      | poly-Si     | A_T    | A_A                     |             | Out               |
| (Mellit, Massi Pavan, and Lugi 2014) | P      | poly-Si     | A_T    | A_A                     |             | Out               |
| (Shapshough, Dhausodi, and Zualkernan 2019) | P      | mono-Si     | A_T    | A_A                     |             | Out               |
| (Pulipaka, Mani, and Kumar 2016) | P      | NA          | A_T    | A_A                     |             | Out               |
| (Pulipaka and Kumar 2016)    | P      | NA          | A_T    | A_A                     |             | Out               |
| (Mani, Pulipaka, and Kumar 2016) | P      | NA          | A_T    | A_A                     |             | Out               |
| (Oprea and Băra 2020)        | P      | mono-Si     | A_T    | A_A                     |             | Out,S             |
| (Sun, Venugopal, and Brandt 2019) | P      | poly-Si     | A_T    | A_A                     |             | Out               |
| (Lee et al. 2018)            | P      | NA          | A_T    | A_A                     |             | Out               |
| (Lee, Lee, and Kim 2017)     | P      | NA          | A_T    | A_A                     |             | Out               |
| (Cervone et al. 2017)        | P      | NA          | A_T    | A_A                     |             | Out               |
| (Alessandri et al. 2015)     | P      | NA          | A_T    | A_A                     |             | Out,S             |
| (Wolf et al. 2016)           | P      | NA          | A_T    | A_A                     |             | Out               |
| (Shi et al. 2012)            | P      | NA          | A_T    | A_A                     |             | Out               |
| (Hossain et al. 2017)        | P      | poly, mono, TF | A_T    | A_A                     |             | Out               |
| (De Giorgi, Congedo, and Malvoni 2014) | P      | mono-Si     | A_T    | A_A                     |             | Out               |
| (Almontag et al. 2014)       | P      | c-Si        | A_T    | A_A                     |             | Out               |
| (Mellit, Sağlam, and Kologirou 2013) | P      | mono-Si     | A_T    | A_A                     |             | Out               |
| (Izgi et al. 2012)           | P      | mono-Si     | A_T    | A_A                     |             | Out               |
| (Son et al. 2018)            | P      | a-Si        | A_T    | A_A                     |             | Out               |
| (Al-Dahidi et al. 2018)      | P      | NA          | A_T    | A_A                     |             | Out               |
| (Al-Kouz et al. 2019)        | P      | POLY-Si     | A_T    | A_A                     |             | Out               |
| (Arshad et al. 2020)         | P      | mono-Si     | A_T    | A_A                     |             | Out               |
| (Buwei et al. 2018)          | P      | NA          | A_T    | A_A                     |             | S                 |
| (Sun, Venugopal, and Brandt 2018) | P      | NA          | A_T    | A_A                     |             | Out               |
| (Mo et al. 2018)             | P      | NA          | A_T    | A_A                     |             | S                 |
| (Maity, Alam, and Pati 2020) | P      | poly-Si     | A_T    | A_A                     |             | In                |
| (Wen-Tao, Shuai, and Xin-Hui 2017) | P      | poly-Si     | A_T    | A_A                     |             | Out,S             |
| (Lie 2019)                   | P      | poly, mono & a-Si | A_T    | A_A                     |             | Out               |
| (Katoch et al. 2018)         | P      | mono-Si     | A_T    | A_A                     |             | Out,S             |
| (Shaaban et al. 2020)        | P      | poly-Si     | A_T    | A_A                     |             | Out               |
| (Alfadda, Rahman, and Pipattanasonporn 2018) | P      | poly-Si     | A_T    | A_A                     |             | Out               |
| (Javed, Guo, and Figgis 2017) | D      | poly-Si     | A_T    | A_A                     |             | Out               |
| (Khalid, Lee, and Li 2012)   | E      | mono-Si     | A_T    | A_A                     |             | Out               |
| (Heinricht et al. 2020)      | D      | poly-Si     | A_T    | A_A                     |             | Out               |
| (Chakchak and Sabit Cetin 2021) | Irr    | NA          | A_T    | A_A                     |             | Out,S             |
| (Faheal et al. 2019)         | S_T    | poly-Si     | A_T    | A_A                     |             | Out,S             |
| (Feng et al. 2020)           | IRR    | mono-Si     | A_T    | A_A                     |             | Out,S             |
| (Ramli, Twaha, and Al-Turki 2015) | IRR    | NA          | A_T    | A_A                     |             | Out               |
| (Zitouni et al. 2021)        | D      | Thin F      | A_T    | A_A                     |             | Out               |
| (Laabbi et al. 2019)         | D      | poly-Si     | A_T    | A_A                     |             | Out               |
| (Kapucu and Cubukcu 2021)    | P      | poly-Si     | A_T    | A_A                     |             | Out               |
| (Dassler et al. 2019)        | E      | Si Bifacial | A_T    | A_A                     |             | Out               |
| (Chiteka, Arora, and Sridhara 2020) | D      | poly-Si     | A_T    | A_A                     |             | Out               |
| (Simal Pérez, Alonso-Montesinos, and Batilles 2021) | D      | poly-Si     | A_T    | A_A                     |             | Out               |
| (Shuho et al. 2019)          | A_T    | mono-Si     | A_T    | A_A                     |             | Out               |
| (Fan et al. 2020)            | P_T    | poly-Si     | A_T    | A_A                     |             | Out               |
| (Bandong et al. 2019)        | PR     | NA          | A_T    | A_A                     |             | Out               |
models, SVM, DT, and ELM techniques were used when input data is numerical, while deep learning models where applied when inputs are images or videos such as the cloud movement and shading factors. Moreover, some techniques require large data sets such as ANN and prone of overfitting.

Based on the reviewed articles, the following points were observed:

- Several PV technologies were used in these studies including monocrystalline (MCP), polycrystalline (PCP), bifacial, or thin film (TFP) (amorphous silicon). Some of the studies have considered more than one type of panel for comparison purposes (Omar Nour-eddine et al. 2021; Hossain et al. 2017; Lie 2019; Graditi, Ferlito, and Adinolfi 2016).
- Across all the operational and performance factors, power has been the most commonly predicted measure; this may be due to its importance and/or the ease of measuring it through the monitoring devices. Nevertheless, other performance indicators were forecasted by few studies such as the energy yield (Dassler et al. 2019), PV panel’s temperature (Fan et al. 2020), operational fault (Kapucu and Cubukcu 2021), and efficiency (Chow, Lee, and Li 2012). This observation would raise the need to predict more than one performance indicator for the same setup to accurately assess performance and compare the accuracy in prediction amongst them as well as include other important factors such as performance ratio. Keeping in mind that efficiency is related to all the equipment used including panels, inverters, and cables while performance ratio is a more reliable measure related to the change in the meteorological data compared to the predicted ones for the same location.
- Despite its effectiveness and flexibility in prediction, machine learning tools usage was limited to solar irradiance (Feng et al. 2020; Shuvho et al. 2019; Ramli, Twaha, and Al-Turki 2015; Chakchak and Sabit Cetin 2021; Alfadda, Rahman, and Pipattanasomporn 2018), shading fault (Fadhel et al. 2019), and clouds movement (Katoch et al. 2018). Other performance indicators such as power, energy, current or environmental factors such as ambient temperature, wind speed or direction, or humidity did not fully utilise the power of ML and DL.
- The majority of studies used ambient temperature and solar irradiance as inputs to predict performance indicators. Although these two factors are the most influential one, other factors should be investigated.
- Other operational factors were rarely considered as inputs in the prediction models despite their important impact on the overall efficiency and performance such as scheduled cleaning cycles (Buwei et al. 2018), and operational fault (Katoch et al. 2018).
- To the best of the authors’ knowledge, PV age or performance degradation factor was not considered as an input in the analysis of the predicting models. There are several studies conducted on PV projects that were installed a long time before the experiment has taken place. Such cases would miss an important input that justifies part of the performance losses.
- Depending on input data correlation and presence of noise, data pre-processing might be necessary. Some studies utilised some commonly known pre-processing tools such as feature selection (FS) and principal component analysis (PCA) (Fadhel et al. 2019; Ziane et al. 2021; Touati et al. 2017). Compared to the number of models used in surveyed literature, pre-processing was not used enough.
- Despite the work that has been done to date, more advanced machine learning and deep learning models can be utilised and combined in a hybrid form of predictive models to predict dust accumulation and other performance indicators while considering environmental, design, operational, and ageing factors. The usage of live videos or photos over time can be very effective in predicting dust accumulation and power losses.

In addition to direct PV performance models, various studies were conducted to forecast the weather and environmental variables that influence the performance of PV systems without including a PV system but relying on historical meteorological factors. For example, the solar irradiance was investigated and predicted by several studies using artificial intelligence techniques such as Kernel Ridge Regression (KRR) (Moreno, Gilabert, and Martinez 2011), DT (Arora, Gambhir, and Kaur 2020), and a combination of different deep learning techniques including MLP, CNN, and RNN for solar irradiance prediction in Korea (Muhammad et al. 2019).

It should be noted that most of the models have frequently considered few input factors such as ambient temperature and solar irradiance, yet it is known that the prediction accuracy is enhanced by adding more influential input factors, which is recommended to consider for future research to have a comprehensive set of meteorological, operational, and design factors.

Also, comparing the accuracy of different predictive models should take into consideration the characteristics of the included inputs, the sample size, the duration of study, and the robust application of preprocessing techniques prior to real modelling. By following such structured and standardised approach, conflicting comparative results can be avoided.

IX. Research gaps

Based on reviewing the related research papers, several research gaps have been clearly identified, starting with the reported quantified performance losses due to soiling in PV panels, there is considerable difference in the losses for the same period of study, which would be caused by the influence of other factors in promoting the dust accumulation on PV panels, or the lack of control in cleaning cycles. Therefore, to enhance the quantification process of soiling losses, all the influential factors including location, weather conditions, design parameters, cleaning, etc. should be included.

Additionally, it was noticed that when comparing different PV technologies such as crystalline panels (mono or poly crystalline), thin film, and CSP, the soiling losses are not similar in different locations or periods of study, which would open the door for more structured comparative research taking into consideration all the factors that affect soiling and monitor them for different PV
technology under same circumstances; this would provide an enhanced outcome that would benefit PV contractors and designers in the selection process for PV panels for specific locations.

Also, a common observation in the reviewed literature is the relatively short periods of study. Since the PV systems are exposed to all dominant weather conditions wherever they are installed, considering at least 1 year of collected data for all the meteorological data would set a solid base for reliable models and outcomes, where the results would be generalisable for the beneficiary entities including contractors, suppliers, designers, and operation and maintenance; as the resulting model covers all the seasonal changes that take place during the year and the extreme weather conditions that affect PV systems. Moreover, controlled environments such as laboratory would serve the purpose of studying certain factors, yet, they have a limited control of the combined effect of several noncontrollable factors like wind speed, dust accumulation, intensity of solar irradiance, humidity, etc. Therefore, outdoor experiments and real time-series input data would result in more accurate models and more reliable outcomes.

Nevertheless, the review has shown a good deal of research studies that focused on certain influential factors which are solar irradiance and dust accumulation, yet several research studies have confirmed the significant contribution of other factors to dust accumulation in PV panels, as well as the severe impact on the performance of PV panels due to this combined effect. Few research studies have been conducted to study all these factors simultaneously and for a scientifically sufficient period. These factors would include weather conditions, design parameters, installation settings, and location characteristics.

Although there is a good deal of research regarding the cleaning methods and materials for PV panels, pre-scheduled cleaning cycles are still dominant for medium to large-scale PV projects. There is a significant need for an accurate schedule for cleaning cycles that is driven by robust predictive models, where all the influencing factors are considered as inputs in the models for at least 1 year. Accurate scheduling for the cleaning would enhance the economical and performance indicators for PV systems.

In addition, the reviewed predictive models for the performance of PV panels were focused on few performance indicators which are mainly the output power or the efficiency. These factors are of high importance, yet they differ across PV systems based on the type of panels or other supporting equipment such as inverters. It would be more reliable to use the performance ratio as a performance indicator, it takes into consideration the impact of meteorological factors and location characteristics, also, it is the most used indicator by PV consultants for assessing the performance of PV systems. Likewise, to enhance the accuracy of the predictive models, all the influencing factors should be considered, also, different type of data including but not limited to real-time images and videos for dust accumulation, clouds movement, fogs, etc. which requires multiple models to process such data.

X. Conclusion and future research

Recent literature focused on dust and other environmental factors’ impact on the performance of PV systems is reviewed and discussed. Statistical and artificial intelligence models employed to predict the performance of PV panels or environmental factors were investigated. The review revealed many aspects that were frequently investigated along with other aspects that are worthy of further investigation.

The performance of PV panels is expressed by several metrics which depend mainly on the short circuit current (Isc) and open circuit voltage (Voc) for the panel or string of panels. Such performance metrics are affected by multiple design and environmental factors including tilt angle, azimuth angle, ambient temperature, solar irradiance, humidity, wind speed and direction, and dust accumulation. The review suggests a strong correlation between these factors that leads to a practical justification for performance losses when they are considered simultaneously. However, very few studies investigated PV performance while including all of these factors. Flexibility of machine and deep learning models can overcome the complexity of predicting PV performance as a function of all input variables.

There are a significant number of studies that disregarded the importance of including all the seasonal changes in environmental and weather conditions over one or several years of study. Many studies covered only a short period of the year which limits its external validity.

Additionally, the review highlighted discrepancies between studies investigating same PV panels technologies. These discrepancies can be attributed to the period of study, inclusion of all significant factors, or testing procedures in the case of controlled indoor experiments. This opens the door for standardising testing procedures and emphasizes the need to use panels specific metrics such as ratio.

Cleaning is a significant activity in PV projects as it affects both their performance and feasibility. Cleaning techniques were extensively investigated in literature with different levels of details and focus. The majority of PV cleaning is done based on pre-scheduled frequencies. Therefore, there is a need to develop an optimised cleaning schedules and techniques based on the specific characteristics of different PV projects. There is also a room for more studies focused on comparing different cleaning methods from an economic standpoint such as benefit-to-cost ratio or payback period.

Finally, several preventive methods have been discussed and applied in the development stage on PV panels including the application of anti-reflective coating and self-cleaning coating, while the research is open regarding the effective coating materials for different installation settings and locations. In addition, other measures such as installation tilt angle and azimuth angle have an impact on power generation as well as the initial cost of the system. Therefore, adopting them should be accompanied by a techno-economic analysis to assure comprehensive assessment.

Notes
1. P:power, E: Energy
2. Same study showed 30–40% losses indoor and 4–5% outdoor

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Notes on contributors

Haneen Abuzaid is a Ph.D. student in the industrial engineering department at the University of Sharjah. Have a previous experience with PV systems design and operation, and interested in optimizing the performance and efficiency of PV systems by tackling the problems and obstacles that negatively affect the performance of such systems.

Mahmoud Awad has more than fifteen years of industrial experience. Prior to academia, he worked at Ford Motor Company, Case New Holland (CNH), and Schlumberger Technology in different technical and management capacities. He also worked as a visiting professor and chair of the Industrial Engineering Department at AlHosen University in Abu Dhabi. His research interests include Design for Six Sigma (DFSS), reliability allocation, Prognostic Health Management (PHM), and Centered-based Maintenance (RCM).

Abdulrahim Shamayleh’s research interests are operation research in healthcare, scheduling, supply chain management, and facilities planning and design. He is a Certified Supply Chain Professional and instructor from the American Association for Operations Management (APICS).

ORCID

Haneen Abuzaid http://orcid.org/0000-0003-1537-0875
Mahmoud Awad http://orcid.org/0000-0003-2999-9084
Abdulrahim Shamayleh http://orcid.org/0000-0002-0214-7052

References

Adinoyi, M. J., and S. A. M. Said. 2013. “Effect of Dust Accumulation on the Power Outputs of Solar Photovoltaic Modules.” Renewable Energy 60: 633–636. doi:10.1016/j.renene.2013.06.014.
Ahmad, M. W., M. Moursheed, and Y. Rezgui. 2018. “Tree-based Ensemble Methods for Predicting PV Power Generation and Their Comparison with Support Vector Regression.” Energy 164: 465–474. doi:10.1016/j.energy.2018.08.207.
Ahmed, Z., H. A. Kazem, and K. Sopian. 2013. “Effect of Dust on Photovoltaic Performance: Review and Research Status.” Latest Trends Renewable Energy Network Informatics 193–199.
Ahmad, K., A. Kitamura, F. Yamamoto, H. Okamoto, H. Takakura, and Y. Hamakawa. 1997. “Outdoor Performance of Amorphous Silicon and Poly crystalline Silicon PV Modules.” Solar Energy Materials Solar Cells 46 (3): 209–218. doi:10.1016/S0927-0248(97)00003-2.
Akkur, R. K., R. Saidur, H. W. Ping, and K. R. Ullah. 2013. “Comparative Study of Stand-alone and Hybrid Solar Energy Systems Suitable for Off-grid Rural Electrification: A Review.” Renewable Sustainable Energy Review 27: 738–752. doi:10.1016/j.rser.2013.06.043.
Al-Amri, A. S., A. Ghazi, and F. Mustafa. “Dust Effects on the Performance of PV Street Light in Baghdad City.” 2013 in International Renewable and Sustainable Energy Conference (IRSEC), Quarzarate, Morocco, pp. 18–22. doi:10.1109/IRSEC.2013.6529687.
Al-Dahidi, S., O. Ayadi, J. Aede, M. Alrbai, and B. Qawasmeh. 2018. “Extreme Learning Machines for Solar Photovoltaic Power Predictions.” Energies 11 (10): 2725. doi:10.3390/en11102725.
Al-Dowsari, A., R. Bkayrat, H. AlZain, and T. Shahin. “Best Practices for Mitigating Soiling Risk on PV Power Plants.” 2014 in Saudi Arabia Smart Grid Conference (SASG), Jeddah, Saudi Arabia, pp. 1–6.
Alessandrini, S., L. Delle Monache, S. Sperati, and G. Gervone. 2015. “An Analog Ensemble for Short-term Probabilistic Solar Power Forecast.” Applied Energy 157: 95–110. doi:10.1016/j.apenergy.2015.08.011.
Alfadda, A., S. Rahman, and M. Pippattasomporn. 2018. “Solar Irradiance Forecast Using Aerosols Measurements: A Data Driven Approach.” Solar Energy 170: 924–939. doi:10.1016/j.solener.2018.05.089.
Al-Hasan, A. Y., and A. A. Ghoneim. 2005. “A New Correlation between Photovoltaic Panel’s Efficiency and Amount of Sand Dust Accumulated on Their Surface.” International Journal Sustain. Energy 24 (4): 187–197. doi:10.1080/14786450500291834.
Al-Housani, M., Y. Bicer, and M. Koç. 2019. “Experimental Investigations on PV Cleaning of Large-scale Solar Power Plants in Desert Climates: Comparison of Cleaning Techniques for Drone Retrofitting.” Energy Conversion and Management 185: 800–815. doi:10.1016/j.enconman.2019.01.058.
Al-Roswal, W., S. Al-Dahidi, B. Hammad, and M. Al-Abed. 2019. “Modeling and Analysis Framework for Investigating the Impact of Dust and Temperature on PV Systems’ Performance and Optimum Cleaning Frequency.” Applied Science 9 (7): 1397. doi:10.3390/app9071397.
Al-Maamary, H. M. S., H. A. Kazem, and M. T. Chaihan. 2017. “The Impact of Oil Price Fluctuations on Common Renewable Energies in GCC Countries.” Renewable Sustainable Energy Review 75: 989–1007. doi:10.1016/j.rser.2016.11.079.
Almonacid, F. P. J. Pérez-Higuera, E. F. Fernández, and L. Hontoria. 2014. “A Methodology Based on Dynamic Artificial Neural Network for Short-term Forecasting of the Power Output of a PV Generator.” Energy Conversion and Management 85: 389–398. doi:10.1016/j.enconman.2014.05.090.
Alonso-Abella, M. F., Chenlo, G. Nofuentes, and M. Torres-Ramírez. 2014. “Analysis of Spectral Effects on the Energy Yield of Different PV (Photovoltaic) Technologies: The Case of Four Specific Sites.” Energy 67: 435–443. doi:10.1016/j.energy.2014.01.024.
Al-Sabounchi, A. M., S. A. Yalyali, and H. A. Al-Thani. 2013. “Design and Performance Evaluation of a Photovoltaic Grid-connected System in Hot Weather Conditions.” Renewable Energy 53: 71–78. doi:10.1016/j.renene.2012.10.039.
Al-Shahri, O. A., M. S. H. Lipu, A. Q. Al-Shetwi, R. A. Begum, N. F. O. Al-Muhesen, E. Soujieri, et al. 2021. “Solar Photovoltaic Energy Optimization Methods, Challenges and Issues: A Comprehensive Review.” Journal Cleaner Production 284:456–468. doi:10.1016/j.jclepro.2020.125465.
Al Shehri, A., B. Parrott, P. Carrasco, H. Al Saiari, and I. Taie. 2016. “Impact of Dust Deposition and Brush-based Dry Cleaning on Glass Transmittance for PV Modules Applications.” Solar Energy 135: 317–324. doi:10.1016/j.solener.2016.06.005.
Al Shehri, A., B. Parrott, P. Carrasco, H. Al Saiari, and I. Taie. 2017. “Accelerated Testbed for Studying the Wear, Optical and Electrical Characteristics of Dry Cleaned PV Solar Panels.” Solar Energy 146: 8–19. doi:10.1016/j.solener.2017.02.014.
Al Siyabi, I. A. Al Mayasi, A. Al Shukali, and S. Khanna. 2021. “Effect of Soiling on Solar Photovoltaic Performance under Desert Climatic Conditions.” Energies 14 (3): 659. https://www.mdpi.com/1996-1073/14/3/659.
Al Siyabi, I., S. Khanna, S. Sundaram, and T. Mallick. 2019. “Experimental and Numerical Thermal Analysis of Multi-layered Microchannel Heat Sink for Concentrating Photovoltaic Application.” Energies 12 (1): 122. doi:10.3390/en12010122.
Al-Waeli, A. H. A., M. T. Chaihan, H. A. Kazem, and K. Sopian. 2017a. “Comparative Study to Use nano-(Al2O3, CuO3, and SiC) with Water to Enhance Photovoltaic Thermal PV/T Collectors.” Energy Conversion and Management 148: 963–973. doi:10.1016/j.enconman.2017.06.072.
Al-Waeli, A. H. A., M. T. Chaihan, H. A. Kazem, K. Sopian, I. Ibrahim, S. Mat, M. H. Ruslan, et al. 2018. “Comparison Study of Indoor/outdoor Experiments of a Photovoltaic Thermal PV/T System Containing SiC Nanofluid as a Coolant”. Energy 151: 33–44. doi:10.1016/j.energy.2018.03.040.
Al-Waeli, A. H. A., K. Sopian, M. T. Chaihan, H. A. Kazem, H. A. Hasan, and A. N. Al-Shamani. 2017b. “An Experimental Investigation of SiC Nanofluid as a Base-fluid for a Photovoltaic Thermal PV/T System.” Energy Conversion and Management 142: 547–558. doi:10.1016/j.enconman.2017.03.076.
Ameur, A., A. Berrada, K. Louidiy, and M. Aggour. 2020. “Forecast Modeling and Performance Assessment of Solar PV Systems.” Journal Cleaner Production 267:122167. doi:10.1016/j.jclepro.2020.122167.
Anderson, M., et al. 2010. “Robotic Device for Cleaning Photovoltaic Panel Arrays.” In Mobile Robotics: Solutions and Challenges, 367–377. Istanbul, Turkey: World Scientific.
Appels, R., B. Lefèvre, B. Herteleer, H. Goyerde, A. Beerten, R. Paesen, K. De Medts, et al. 2013. “Effect of Soiling on Photovoltaic Modules.” Solar Energy 96: 283–291. doi:10.1016/j.solener.2013.07.017.
Investigations, Results, Literature, and Mitigation Approaches.” Renewable Sustainable Energy Review 22: 698–733. doi:10.1016/j.rser.2012.12.065.

Sasitharanuwat, A., W. Rakwichian, N. Ketjot, and S. Yammen. 2007. “Performance Evaluation of a 10kWp PV Power System Prototype for Isolated Building in Yathalld.” Renewable Energy 32 (8): 1288–1300. doi:10.1016/j.renene.2006.05.002.

Sayyah, A., M. N. Horenstein, and M. K. Mazumder. 2014. “Energy Yield Loss Caused by Dust Deposition on Photovoltaic Panels.” Solar Energy 107: 576–604. doi:10.1016/j.solener.2014.05.030.

Scully, T. and A. J. Wilson. 2011. “Atmospheric Dust Deposition Losses of Thin Film PV Modules.” Procedia Environmental Science 15: 463–470. doi:10.1016/j.proenv.2011.09.085.

Sharma, V., and S. S. Chandel. 2013. “Performance and Degradation Analysis for Long Term Reliability of Solar Photovoltaic Systems: A Review.” Renewable Sustainable Energy Review 27: 753–767. doi:10.1016/j.rser.2013.07.046.

Sharma, V., and S. S. Chandel. 2016a. “A Novel Study for Determining Early Life Degradation of Multi-crystalline-silicon Photovoltaic Modules Observed in Western Himalayan Indian Climatic Conditions.” Solar Energy 134: 32–44. doi:10.1016/j.solener.2016.04.023.

Sharma, V., A. Kumar, O. S. Saxtry, and S. S. Chandel. 2013. “Performance Assessment of Different Solar Photovoltaic Technologies under Similar Outdoor Conditions.” Energy 58: 511–518. doi:10.1016/j.energy.2013.05.068.

Shi, J., W.-J. Lee, Y. Liu, Y. Yang, and P. Wang, 2012. “Forecasting Power Output of Photovoltaic Systems Based on Weather Classification and Support Vector Machines.” IEEE Transactions on Industry Applications 48 (3): 1064–1069. doi:10.1109/TIA.2012.2190816.

Shuvo, M. B. A., M. A. Chowdhury, S. Ahmed, and M. A. Kashem. 2019. “Prediction of Solar Irradiation and Performance Evaluation of Grid Connected Solar 80Kwp PV Plant in Bangladesh.” Energy Reports 5: 714–722. doi:10.1016/j.enrep.2019.06.011.

Siddiqui, R., R. Kumar, G. K. Jha, G. Gowri, M. Morampudi, P. Rajput, S. Lata, et al. 2016. “Comparison of Different Technologies for Solar PV (Photovoltaic) Outdoor Performance Using Indoor Accelerated Aging Tests for Long Term Reliability.” Energy 107:550–561. doi:10.1016/j.energy.2016.04.054.

Simal Pérez, N., J. Alonso-Montesinos, and F. J. Batlle. 2021. “Estimation of Soiling Losses from an Experimental Photovoltaic Plant Using Artificial Intelligence Techniques.” Applied Science 11 (4): 1516. doi:10.3390/app11041516.

Singh, G. K., S. A. Sulaiman, and A. K. Singh. 2013. “Solar Power Generation by PV (Photovoltaic) Technology: A Review.” Energy 53: 1–13. doi:10.1016/j.energy.2013.02.057.

Smestad, G. P., et al. 2020. “Modelling Photovoltaic Soiling Losses through Optical Characterization.” Science Reports 10 (1): 1–13. DOI:10.1038/s41598-019-56688-z.

Solar_Feed, “Concentrated Solar Power (CSP) Vs Photovoltaic (PV): All In-depth Comparison,” Sol. Feed, 2019, [Online]. Available: https://solarfeeds.com/csp-and-pv-differences-comparison/#:~:text=CSP is an indirect method,of the sun’s light instead.

Son, J., et al. 2012. “A Practical Superhydrophilic Self Cleaning and Antireflective Surface for Outdoor Photovoltaic Applications”. Solar Energy Materials Solar Cells 98: 46–51. 10.1016/j.solmat.2011.10.011.

Song, Z., J. Liu, and H. Yang. 2021. “Air Pollution and Soiling Implications for Solar Photovoltaic Power Generation: A Comprehensive Review.” Applied Energy 298: 117247. doi:10.1016/j.apenergy.2021.117247.

Son, J., Y. Park, J. Lee, and H. Kim. 2018. “Sensorless PV Power Forecasting in Grid-connected Buildings through Deep Learning.” Sensors 18 (8): 2529. doi:10.3390/s18082529.

Sonusz, O., E. Aduigzel, R. O. Kabaqolgu, and A. Ersoy. 2020. “The Effect Of Pollution On Photovoltaic Panels Under Climate Conditions In Hatay.” Erzincan Universitesi Fen Bilim. Enstitüüsü Derg 13 (3): 1413–1423.

Sulaiman, S. A., H. H. Hussain, N. S. H. Nik Leh, and M. S. I. Razali. 2011. “Effects of Dust on the Performance of PV Panels.” World Academic Science Technology and Development Journal (WASTD) 11 (1): 273–277. doi:10.1016/j.egypro.2014.06.006.

Sulaiman, S. A., A. K. Singh, M. M. Mokhtar, and M. A. Bou-Rabee. 2014. “Influence of Dust Accumulation on Performance of PV Panels.” Energy Procedia 60: 50–56. doi:10.1016/j.egypro.2014.06.006.

Sun, K., L. Lu, Y. Jiang, Y. Wang, K. Zhou, and Z. He. 2018. “Integrated Effects of PM2.5 Deposition, Module Surface Conditions and Nanocoatings on Solar PV Surface Glass Transmittance.” Renewable Sustainable Energy Review 82: 4107–4120. doi:10.1016/j.rser.2017.10.062.

Sun, Y., V. Venugopal, and A. R. Brandt, “Convolutional Neural Network for Short-term Solar Panel Output Prediction.” 2018in 2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC)(A Joint Conference of 45th IEEE PVSC, 28th PVSEC & 34th EU PVSEC), Hawaii, pp. 2357–2361.

Sun, Y., V. Venugopal, and A. R. Brandt. 2019. “Short-term Solar Power Forecast with Deep Learning: Exploring Optimal Input and Output Configuration.” Solar Energy 188: 730–741. doi:10.1016/j.solener.2019.06.041.

Supe, H., R. Avtar, D. Singh, A. Gupta, A. P. Yunus, J. Dou, A. A. Ravankar, et al. 2020. “Google Earth Engine for the Detection of Soiling on Photovoltaic Solar Panels in Arid Environments.” Remote Sensors 12 (9): 1466. DOI:10.3390/rs12091466.

Tagawa, K. 2012. “Effect of Sand Erosion of Glass Surface on Performances of Photovoltaic Module.” Sustainable Research Innovation Processing 4.

Tanesj, J., D. Parlevliet, J. Whale, and T. Urmee. 2016. “Dust Effect and Its Economic Analysis on PV Modules Deployed in a Temperate Climate Zone.” Energy Procedia 100: 65–68. doi:10.1016/j.egypro.2016.10.154.

Tanesj, J., D. Parlevliet, J. Whale, and T. Urmee. 2018. “Energy and Economic Losses Caused by Dust on Residential Photovoltaic (PV) Systems Deployed in Different Climate Areas.” Renewable Energy 120: 401–412. doi:10.1016/j.renene.2017.12.076.

Tanesj, J., D. Parlevliet, J. Whale, and T. Urmee. 2019. “The Effect of Dust with Different Morphologies on the Performance Degradation of Photovoltaic Modules.” Sustainable Energy Technology Assessments 31: 347–354. doi:10.1016/j.seta.2018.12.024.

Tanesj, J., D. Parlevliet, J. Whale, T. Urmee, and T. Pryor. 2015. “The Contribution of Dust to Performance Degradation of PV Modules in a Temperate Climate Zone.” Solar Energy 120: 147–157. doi:10.1016/j.solener.2015.06.052.

Touati, F., et al. 2017. “Long-term Performance Analysis and Power Prediction of PV Technology in the State of Qatar.” Renewable Energy 113:952–965. doi:10.1016/j.renene.2017.06.078.

Touati, F., M. Al-Hitmi, and H. Bouchech, “Towards Understanding the Effects of Climatic and Environmental Factors on Solar PV Performance in Arid Desert Regions (Qatar) for Various PV Technologies,” 2012 in 2012 First International Conference on Renewable Energies and Vehicular Technology, Nabeul, Tunisia, pp. 78–83, doi:10.1109/REVET.2012.6195252.

Tranfield, D., D. Denyer, and P. Smart. 2003. “Towards a Methodology for Developing Evidence-informed Management Knowledge by Means of Systematic Review.” British Journal Management 14 (3): 207–222. doi:10.1111/1467-8551.00375.

Tyagi, V. V., N. A. A. Rahim, N. A. Rahim, A. Jeyraj, and L. Selvaraj. 2013. “Progress in Solar PV Technology: Research and Achievement.”
Wolff, A., A. Amin, T. Haider, M. Saleem, and N. Z. Butt. 2020. “Investigation of Soiling Effects, Dust Chemistry and Optimum Cleaning Schedule for PV Modules in Lahore, Pakistan.” Renewable Energy 150: 456–468. doi:10.1016/j.renene.2019.12.090.

Urejola, E., J. Antonanzas, P. Ayala, M. Salgado, G. Ramírez-Sagner, C. Cortés, A. Pino, et al. 2016. “Effect of Soiling and Sunlight Exposure on the Performance Ratio of Photovoltaic Technologies in Santiago, Chile.” Energy Conversion and Management 114: 338–347. doi:10.1016/j.enconman.2016.02.016.

Ustun, T. S., Y. Nakamura, J. Hashimoto, and K. Otani. 2019. “Performance Analysis of PV Panels Based on Different Technologies after Two Years of Outdoor Exposure in Fukushima, Japan.” Renewable Energy 136: 159–178. doi:10.1016/j.renene.2018.12.100.

Vázquez, M., and I. Rey-Stolle. 2008. “Photovoltaic Module Reliability Model Based on Field Degradation Studies.” Progress in Photovoltaics: Research and Applications 16 (5): 419–433. doi:10.1002/pip.825.

Wen-Tao, Z., W. Shuai, and D. Xin-Hui. 2017. “Research of Power Prediction about Photovoltaic Power System: Based on Bp Neural Network.” Multi-Criteria Analysis Air Pollution Urban Environmental Due Road Traffic 18: 1614–1623.

Wilson, N. R., L. M. Norman, M. Villarreal, L. Gass, R. Tiller, and A. Sahyoun. 2016. “Comparison of Remote Sensing Indices for Monitoring of Desert Cienegas.” Arid Land Research and Management 30 (4): 460–478.

Wolf, B., J. Kühnert, E. Lorenz, O. Kramer, and D. Heinemann. 2016. “Comparing Support Vector Regression for PV Power Forecasting to a Physical Modeling Approach Using Measurement, Numerical Weather Prediction, and Cloud Motion Data.” Solar Energy 135: 197–208. doi:10.1016/j.solener.2016.05.051.

Wu, Y., J. Du, G. Liu, D. Ma, F. Jia, J. J. Klemeš, J. Wang, et al. 2022. “A Review of Self-cleaning Technology to Reduce Dust and Ice Accumulation in Photovoltaic Power Generation Using Superhydrophobic Coating.” Renewable Energy 185:1034–1061. doi:10.1016/j.renene.2021.12.123.

Wu, T.-C., Y.-S. Long, S.-T. Hsu, and E.-Y. Wang. 2017. “Efficiency Rating of Various PV Technologies under Different Indoor Lighting Conditions.” Energy Procedia 130: 66–71. doi:10.1016/j.egypro.2017.09.397.

Xu, K., K. Ni, Y. Hu, J. Si, H. Wen, and D. Yu. 2017. “Analysis of the Optimum Tilt Angle for a Soiled PV Panel.” Energy Conversion and Management 148: 100–109. doi:10.1016/j.enconman.2017.05.058.

Yadav, A. K., and S. S. Chandel. 2013. “Tilt Angle Optimization to Maximize Incident Solar Radiation: A Review.” Renewable Sustainable Energy Review 23: 503–513. doi:10.1016/j.rser.2013.02.027.

Yap, W. K., M. Baig, and E. Halawa. “Performance Monitoring and Evaluation of a CIGS Roof-integrated Photovoltaic System under the Unique Tropical Environment of Darwin, Northern Territory,” 2014 in Proceedings of the Asia Pacific Solar Research Conference, Sydney, vol. 114.

Yoo, S.-H. 2011. “Simulation for an Optimal Application of BIPV through Parameter Variation.” Solar Energy 85 (7): 1291–1301. doi:10.1016/j.solener.2011.03.004.

Zahidee, F. M., S. Mekhilif, M. Seyedmahmoudian, and B. Horan. 2016. “Dust as an Unalterable Deteriorative Factor Affecting PV Panel’s Efficiency: Why and How.” Renewable Sustainable Energy Review 65: 1267–1278. doi:10.1016/j.rser.2016.06.068.

Zhang, H., Y. Sun, L. Wu, X. Zhang, and Y. Xiang, “Tracking Mechanism and Cosine Effect Study of Module-Heliosat Solar Collector,” 2016 in 2016 4th International Conference on Machinery, Materials and Information Technology Applications, Xi’an, China, pp. 469–474.

Zhao, W., Y. Lv, Z. Wei, W. Yan, and Q. Zhou. 2021. “Review on Dust Deposition and Cleaning Methods for Solar PV Modules.” Journal Renewable Sustainable Energy 13 (3): 32701. doi:10.1063/5.0053866.

Ziane, A., A. Necabia, N. Sahnoun, R. Dabou, M. Mostefaoui, A. Bouraiou, S. Khelifi, et al. 2021. “Photovoltaic Output Power Performance Assessment and Forecasting: Impact of Meteorological Variables.” Solar Energy 220: 745–757. doi:10.1016/j.solener.2021.04.004.

Zitouni, H., et al. 2021. “Experimental Investigation and Modeling of Photovoltaic Soiling Loss as A Function of Environmental Variables: A Case Study of Semi-arid Climate.” Solar Energy Materials Solar Cells 221: 110874. doi:10.1016/j.solmat.2020.110874.

Zorrilla-Casanova, J., et al. 2011. “Analysis of Dust Losses in Photovoltaic Modules.” World Renewable Energy Congress 2985–2992.