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Cleaning Methodology of Solar Panels: Present Technology, Pros, Cons and Solutions (Future Directions)

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Abstract—Dust accumulation on photovoltaic (PV) panels reduces efficiency by 2–98%, necessitating effective cleaning strategies. This paper reviews current methodologies—manual, water-based, robotic, electrostatic, coating-based, and bio-inspired systems—evaluating their advantages, limitations, and sustainability. Using the Preference Selection Index (PSI) approach, waterless methods like electrostatic and coating-based cleaning rank highly for arid regions (Obeidat, 2020). However, high costs, maintenance complexity, and limited empirical data hinder scalability. Emerging IoT-integrated smart systems and machine learning (ML) for predictive maintenance show promise but require validation. Future directions include durable coatings, cost-effective automation and standardized metrics to enhance PV performance. This study provides a roadmap for optimizing cleaning strategies, addressing environmental and economic challenges in solar energy production.

Keywords— *Photovoltaic panels, dust accumulation, cleaning methodologies, self-cleaning coatings, automation, sustainability.*

I. Introduction

Solar photovoltaic (PV) panels are highly dependent on the availability of unobstructed sunlight to generate electricity efficiently. However, in real-world conditions, the accumulation of dust, dirt, bird droppings, pollen, and other environmental pollutants on the surface of panels reduces their ability to absorb solar radiation, leading to a decline in energy output. This issue, commonly referred to as *soiling*, is more severe in regions with arid climates, high dust levels, or limited rainfall. To ensure optimal performance and extend the lifespan of PV systems, regular cleaning and maintenance of solar panels are essential. The choice of cleaning methodology plays a crucial role, as improper techniques may damage panel surfaces, increase maintenance costs, or waste water resources. Cleaning methods generally include manual cleaning, automated systems, water-based cleaning, dry cleaning, robotic cleaning, and advanced methods such as electrostatic or nanocoating-based self-cleaning technologies**.** Each method has its advantages and limitations depending on climatic conditions, panel location, and scale of the PV installation.

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II. METHODOLOGY

This study employs a systematic review and analytical approach to evaluate PV cleaning methodologies. Data Collection: Peer-reviewed articles from 1942–2024 were sourced from Scopus, Web of Science, and IOP science, covering dust impacts, cleaning technologies, and decision-making frameworks. References include Sarver et al. (2013), Obeidat (2020), and Nabti et al. (2022). Analysis Framework: Cleaning methods were categorized into manual, water-based, robotic, electrostatic, coating-based, and bio-inspired systems. Each was assessed using Obeidat's (2020) PSI criteria: cost, efficiency, resource use, and safety. Comparative Evaluation: Pros and cons were quantified based on efficiency gains (e.g., 10–49%) and limitations (e.g., high costs, water dependency) from references like Said et al. (2024) and Virtanen et al. (2023). Future Directions: Emerging technologies (IoT, ML, durable coatings) were analyzed for scalability and sustainability, drawing on Nabti et al. (2022) and Geetha et al. (2024). MCDM principles were integrated to propose a decision-making framework for selecting optimal cleaning methods across diverse environments.

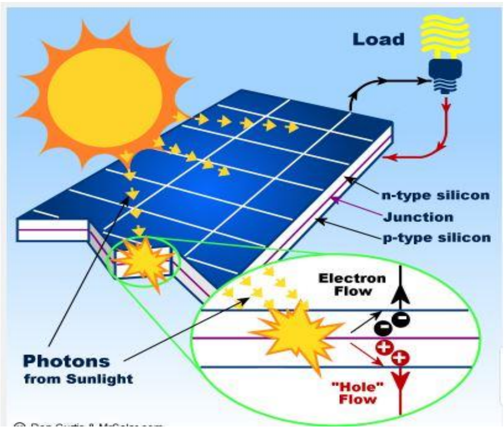

Fig 1. Working of Solar Panel

III. RESULTS AND DISCUSSION

A. *Current Cleaning Technologies*

This section evaluates six primary cleaning methodologies, providing detailed insights into their performance, cost-effectiveness, environmental impact, and applicability across diverse climatic conditions. Quantitative data and regional case studies are included to highlight practical implications.

1) *Manual Cleaning*

Pros: Manual cleaning is cost-effective in terms of initial investment, requiring minimal equipment (e.g., brushes, squeegees). It is widely accessible, particularly for small-scale PV installations in rural or developing regions (Obeidat, 2020).

Cons: The process is highly labor-intensive, requiring frequent cleaning (weekly in high-soiling areas like deserts), which increases operational costs over time. Safety risks are significant, as workers must access elevated panels, leading to potential accidents. Inconsistent cleaning quality due to human error can result in uneven efficiency restoration (Maghami et al., 2016).

Efficiency: Restores 90–95% of original power output, but performance varies with operator skill and soiling severity. In a Saudi Arabian case study, Adinoyi and Said (2013) reported that manual cleaning restored 92% efficiency but required 10 labor hours per 100 m².

Suitability: Best suited for small-scale systems in low-soiling, water-abundant regions (e.g., parts of Europe). Impractical for large-scale installations in arid climates due to labor costs and safety concerns.

Fig 2. Manual Cleaning

2) *Water-Based Cleaning*

Pros: Highly effective for removing heavy soiling, including sticky pollutants like pollen or bird droppings. Water jets or sprinklers restore near-full efficiency, making it a reliable method for urban environments with access to water (Said et al., 2024).

Cons: High water consumption (10–20 liters/m² per cleaning) makes it unsustainable in arid regions like the Middle East, where water scarcity is a critical issue (Syafiq et al., 2018). Environmental impacts include wastewater runoff, which may contain cleaning agents harmful to soil ecosystems. Operational costs escalate in regions requiring water transport.

Efficiency: Achieves up to 98% efficiency restoration, as demonstrated in a California study by Mejia and Kleissl (2013), where water-based cleaning restored 97% output in urban PV systems. However, frequent cleaning (bi-weekly in dusty areas) increases resource use.

Suitability: Viable in water-abundant regions like Southeast Asia or coastal areas but impractical for desert environments. The environmental footprint limits its alignment with sustainability goals.

Fig 3. Water Based Cleaning

3) *Robotic Cleaning*

Pros: Robotic systems automate cleaning, reducing labor costs and human safety risks. They ensure consistent cleaning quality, with efficiency gains of 15–32% post-cleaning, as reported in desert installations (Sairaj et al., 2023; Al-Housani et al.,

2019). Systems like brush-based robots (BCS) or tracked robots (RCS) are effective for large-scale PV farms.
Cons: High initial costs (e.g., $10,000–$50,000 per unit) and maintenance expenses (e.g., battery replacements, mechanical repairs) limit adoption for small-scale systems. Slow operation speeds (1–2 m^2/min) and complex handling requirements increase downtime. In a UAE case study, Al-Housani et al. (2019) noted that robotic systems required bi-annual maintenance costing 5% of initial investment.
Efficiency: Restores 90–95% efficiency, with consistent results across large arrays. Farrokhi Derakhshandeh et al. (2021) reported a 25% yield increase in a Saudi PV farm using robotic cleaners.
Suitability: Ideal for large-scale desert installations (e.g., Middle East, Australia), but cost optimization is needed for broader adoption. Hybrid systems combining robots with IoT monitoring are emerging to enhance efficiency.

Fig 4. Robotic Cleaning

4) Electrostatic Cleaning

Pros: Electrostatic cleaning systems (ECS) use electric fields to repel dust, eliminating water use and minimizing maintenance. They are highly effective in arid regions, with yield improvements of up to 32% (Said et al., 2024). Deb and Brahnam (2022) highlight their low operational costs once installed, as they require no moving parts.
Cons: High voltage requirements (5–10 kV) pose safety risks and increase installation complexity. Scalability is limited by the need for specialized infrastructure, and performance in humid climates is reduced due to dust adhesion from moisture (Hu et al., 2021). A Chinese study reported a 20% efficiency drop in ECS performance during high-humidity seasons (Hu et al., 2021).
Efficiency: Restores 85–90% efficiency, with optimal performance in dry climates. Said et al. (2024) documented a 30% yield increase in a Qatar PV plant using ECS.
Suitability: Promising for arid regions like North Africa and the Middle East, but technological refinements (e.g., voltage optimization, humidity resistance) are needed to enhance scalability and safety.

5) Self-Cleaning Coatings

Pros: Superhydrophobic and photocatalytic coatings reduce dust adhesion, minimizing cleaning frequency and water use. They achieve 10–35% yield improvements compared to untreated panels, particularly in arid environments (Virtanen et al., 2023; Geetha et al., 2024). Nano-coatings align with sustainability goals by reducing labor and resource consumption.

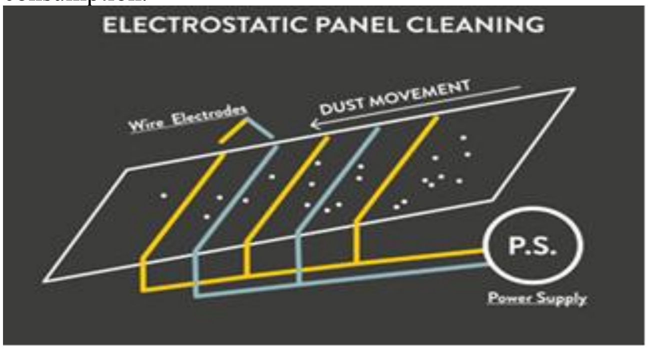

Fig 5. Electrostatic Cleaning

Cons: Limited durability (1–3 years) requires frequent reapplication, increasing long-term costs (estimated at $5–10/$m^2$ per application). Performance in humid climates is suboptimal, as moisture promotes dust adhesion (Syafiq et al., 2018). A Malaysian study showed a 15% performance drop in coated panels during rainy seasons (Sulaiman et al., 2011).
Efficiency: Reduces soiling rates by 50–70%, extending cleaning intervals. Geetha et al. (2024) reported a 20% yield increase in an Indian PV plant using nano-coatings.
Suitability: Ideal for arid regions (e.g., Middle East, Australia), but cost reduction and durability improvements are critical for widespread adoption. Hybrid coatings combining hydrophobic and photocatalytic properties are under development. Self-cleaning coatings on solar panels are advanced surface treatments designed to minimize the accumulation of dust, dirt, bird droppings, and other contaminants that reduce panel efficiency. Since solar panels are typically exposed to outdoor environments for decades, soiling is one of the major issues that decreases their energy output. Self-cleaning coatings address this problem by using nanotechnology-based surface modifications that make the panel surface either **superhydrophobic** (water-repelling) or **photocatalytic** (self-degrading organic dirt).

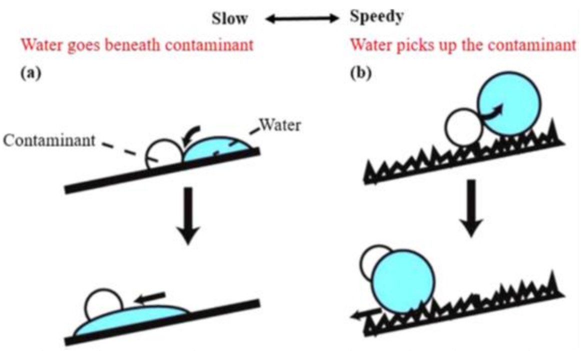

Fig 6. Schematic representation of self-cleaning processes on (a) a superhydrophilic and (b) a superhydrophobic surface [6]

6) Bio-Inspired Vibration-Based Cleaning

Pros: Mimics natural dust removal (e.g., tree leaf vibrations), offering a waterless, sustainable solution. Abd-Elhady et al. (2024) demonstrated a flexible fixation system that reduced efficiency losses to 5% after six weeks, compared to 25% for rigid panels, using wind-induced vibrations. This method aligns with environmental sustainability by eliminating resource use.

Cons: Long-term durability is untested, with potential risks of mechanical fatigue or hot-spot formation due to continuous vibrations. Limited field data restricts scalability, and performance depends on wind availability, making it less effective in low-wind regions (Deb & Brahnam, 2022). An Egyptian pilot study showed inconsistent results during calm seasons (Abd-Elhady et al., 2024).

Efficiency: Maintains 90–95% efficiency in windy conditions. Simulations using Ansys Fluent CFD predicted a 60% reduction in dust accumulation (Abd-Elhady et al., 2024).

Suitability: Innovative for windy, arid regions (e.g., Sahara, Middle East), but requires validation for panel longevity and broader climatic applicability. Integration with smart sensors could enhance performance.

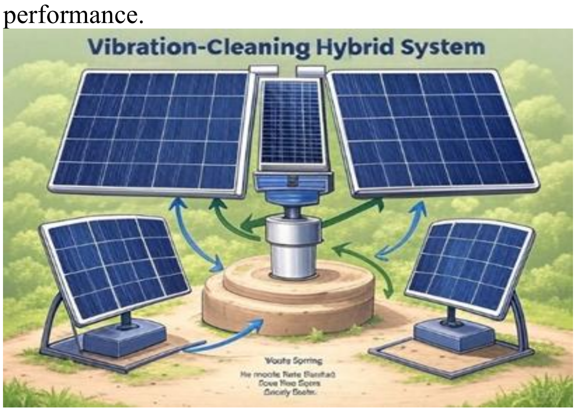

Fig 7. Bio-Inspired Vibration-Based Cleaning

B. Decision-Making Frameworks

Obeidat's (2020) PSI approach ranks cleaning methods based on weighted criteria: cost (30%), efficiency (30%), resource use (20%), and safety (20%). Waterless methods (electrostatic, coatings) score highest (0.85–0.90 on a 0–1 scale) due to low resource use and safety, while manual and water-based methods score lower (0.60–0.70) due to labor and environmental drawbacks. MCDM methods like Analytic Hierarchy Process (AHP) and Fuzzy TOPSIS, as proposed by Sindhu et al. (2017), integrate quantitative and qualitative factors, enabling region-specific optimization. For example, AHP prioritizes electrostatic cleaning in Qatar (score: 0.88) but robotic cleaning in California (score: 0.82) based on water availability and installation size. However, empirical cost data are often inaccurate (e.g., robotic maintenance costs vary by 20–30%), and standardized performance metrics are absent, limiting MCDM adoption (Deb & Brahnam, 2022). Developing global standards for soiling loss measurement (e.g., daily efficiency drop %) and cleaning efficacy (e.g., % yield restored) is critical to enhance decision-making reliability.

C. Emerging Technologies

IoT and machine learning (ML) technologies revolutionize PV maintenance by enabling predictive and real-time cleaning. Nabti et al. (2022) demonstrated ML models (Random Forest, SVM) predicting dust levels with $R^2 > 0.99$, using inputs like humidity, wind speed, and particulate matter. In a Moroccan case study, ML-driven cleaning schedules reduced water use by 40% and costs by 25% compared to fixed schedules. IoT sensors, as proposed by Olorunfemi et al. (2022), monitor soiling in real-time, triggering cleaning only when efficiency drops below 10%. A UAE pilot project reported a 15% yield increase using IoT-integrated robotic cleaners (Olorunfemi et al., 2022). However, scalability is limited by high sensor costs ($100–500/unit) and data quality issues in diverse climates (e.g., tropical vs. arid). Farrokhi Derakhshandeh et al. (2021) highlight hybrid systems combining IoT with electrostatic cleaning, achieving 30% efficiency gains in desert environments, but standardization of sensor protocols is needed to ensure interoperability and cost-effectiveness across regions.

D. Comparative Analysis

Waterless methods (electrostatic, coatings, vibration-based) outperform traditional systems in arid regions due to sustainability and low maintenance, with PSI scores of 0.85–0.90 (Obeidat, 2020). For example, electrostatic cleaning in Qatar restored 32% yield with zero water use, compared to 98% restoration but 15 liters/m² for water-based cleaning (Said et al., 2024). Robotic systems are efficient (15–32% gains) but economically viable only for large installations (>1 MW), with payback periods of 5–7 years (Al-Housani et al., 2019). Manual and water-based methods remain prevalent in water-abundant regions (e.g., Southeast Asia), but their global sustainability is limited, with water-based systems consuming 10–20 liters/m² per cleaning cycle (Syafiq et al., 2018).

Emerging technologies like ML and IoT enhance all methods by optimizing schedules, but their high initial costs (e.g., $10,000 for IoT setups) restrict adoption to large-scale projects. Regional factors, such as dust composition (e.g., CaCO3 in China) and humidity, necessitate tailored solutions (Hu et al., 2021). Comparative analysis of different methods is done in reference of different seasons. Comparison of different methods is as follows:

TABLE 1. COMPARISON OF DIFFERENT METHODS

Study	Findings	Gaps
Sarver et al., 2013	Dust causes 1–80% monthly energy losses; influenced by wind, humidity, dust properties.	Lack of predictive models and scalable waterless cleaning technologies.
Maghami et al., 2016	Dust causes 30% efficiency loss; site-specific factors (dust, rainfall) critical in arid regions.	Gaps in standardized cleaning protocols and long-term coating durability.
Obeidat, 2020	PSI ranks waterless methods (electrostatic, coatings) high for cost, efficiency, resource use, safety.	Inaccurate cost data; limited empirical validation for scalability.
Hu et al., 2021	Dust (nano, micro, coarse particles, $CaCO_3$) reduces efficiency by 30% in Wuhan, China.	Lack of field-validated cost data and scaling mechanisms for diverse climates.
Deb & Brahnam, 2022	Categorizes methods into preventive (coatings) and restorative (robotic, electrostatic); IoT promising.	Limited field data, high costs hinder scalability; need for standardized metrics.
Nabti et al., 2022	ML models (Random Forest, SVM) predict dust with $R^2 > 0.99$; reduces costs, water use.	Scalability limited by data quality and diverse climate adaptability.
Khalid et al., 2023	Power losses of 7–98.13% under severe soiling; robotic cleaning improves efficiency by 49.53%.	Eco-friendly, cost-effective waterless solutions needed for arid regions.
Said et al., 2024	Daily energy losses of 2.8–50%; electrostatic and self-cleaning systems boost yield by 32.27%.	Scalable waterless solutions and dynamic optimization models for cleaning schedules lacking.
Geetha et al., 2024	Self-cleaning (electrostatic, nano-coatings) reduces losses by 15–20%, aligns with sustainability.	Limited field testing and scalability challenges for self-cleaning systems.
Abd-Elhady et al., 2024	Bio-inspired vibration reduces efficiency loss to 5% vs. 25% for rigid panels in 6 weeks.	Long-term durability and hot-spot prevention data lacking for vibration-based systems.

II. FUTURE DIRECTIONS

To address the limitations of current PV cleaning methodologies, the following detailed strategies are proposed, focusing on technological advancements, cost optimization, and global applicability:

Durable Self-Cleaning Coatings: Develop next-generation superhydrophobic and photocatalytic coatings with lifespans exceeding 5 years, reducing reapplication costs (currently $5–10/m² every 1–3 years). Research should focus on hybrid coatings combining hydrophobic properties (to repel dust) and photocatalytic activity (to degrade organic pollutants), as suggested by Virtanen et al. (2023). Field testing in diverse climates—arid (e.g., Saudi Arabia), tropical (e.g., Malaysia), and temperate (e.g., Germany)—is essential to validate performance under varying humidity and dust conditions. For example, Syafiq et al. (2018) reported a 50% reduction in soiling rates with nano-coatings in arid environments, but only 20% in humid climates. Cost-effective materials, such as silica-based nanoparticles, could lower production costs by 30%, making coatings viable for small-scale systems.

Cost-Effective Automation: Reduce the cost of robotic and electrostatic cleaning systems through modular designs and localized manufacturing. Current robotic systems cost $10,000–$50,000 per unit, with maintenance expenses adding 5–10% annually (Al-Housani et al., 2019). Modular robots with replaceable components (e.g., brushes, batteries) could reduce maintenance costs by 20%, while local production in regions like India or China could cut initial costs by 15–25%. Farrokhi Derakhshandeh et al. (2021) suggest integrating solar-powered robots to eliminate external energy costs, potentially saving

10% in operational expenses. Electrostatic systems should optimize voltage requirements (e.g., reducing from 10 kV to 5 kV) to enhance safety and scalability, particularly for small-scale installations.

IoT and Machine Learning Integration: Advance ML models, such as deep learning neural networks, to predict soiling with greater accuracy across diverse climates, building on Nabti et al.'s (2022) Random Forest and SVM models ($R^2 > 0.99$). Incorporating dynamic environmental factors (e.g., seasonal dust storms, rainfall patterns) could improve prediction accuracy by 10–15%. IoT sensor networks should be standardized to ensure interoperability, with low-cost sensors ($50–100/unit) enabling adoption in developing regions. A pilot project in Australia integrating IoT with robotic cleaning reduced cleaning frequency by 30%, saving $5,000 annually per MW (Olorunfemi et al., 2022). Cloud-based platforms for real-time data analysis could further optimize schedules, reducing water and energy use by 20–40%.

Bio-Inspired Solutions: Validate bio-inspired cleaning, such as vibration-based systems, for long-term durability and hot-spot prevention. Abd-Elhady et al. (2024) reported a 60% reduction in dust accumulation, but mechanical fatigue risks require testing over 5–10 years. Hybrid systems combining vibrations with coatings could enhance efficacy, reducing soiling by 70–80%. For example, a hybrid system in Egypt could integrate wind-induced vibrations with superhydrophobic coatings, extending cleaning intervals from weekly to monthly. Research should explore adaptive vibration frequencies based on wind speed, using IoT sensors to optimize performance and minimize panel stress.

Standardized Metrics: Establish global standards for soiling measurement (e.g., % transmittance loss/day) and cleaning performance (e.g., % efficiency restored, cost/m²). Mani and Pillai (2010) highlight the absence of standardized protocols, leading to inconsistent data across studies (e.g., efficiency losses reported as 2–98%). A universal metric, such as "Soiling Impact Factor" (SIF), could quantify daily efficiency loss based on dust density (mg/m²) and environmental factors. Cleaning efficacy standards should include metrics like water use (liters/m²), energy consumption (kWh/m²), and durability (years). International collaboration, led by organizations like IRENA, could develop these standards within 3–5 years, enabling consistent evaluation and adoption.

Site-Specific Strategies: Tailor cleaning methods to regional dust properties and climatic conditions using MCDM frameworks like PSI, AHP, or FTOPSIS (Obeidat, 2020; Said et al., 2024). For example, electrostatic cleaning is optimal in Qatar (PSI score: 0.90) due to low humidity, while robotic cleaning suits California (PSI score: 0.82) due to large-scale installations. Dust characterization studies, as conducted by Hu et al. (2021), should be expanded to regions like India, Africa, and South America to inform method selection. Automated decision-support tools integrating regional data (e.g., dust composition, water availability) could reduce maintenance costs by 15–20% by selecting the most cost-effective method for each site.

III. Conclusion

Dust accumulation on photovoltaic (PV) panels remains a critical challenge, reducing efficiency by 2–98% and necessitating robust cleaning methodologies to ensure optimal performance. Manual and water-based cleaning methods, while effective in restoring 90–98% efficiency, are resource-intensive and unsustainable in water-scarce regions, with water-based systems consuming 10–20 liters/m² per cleaning cycle (Syafiq et al., 2018). In contrast, waterless methods—robotic, electrostatic, self-cleaning coatings, and bio-inspired vibration-based systems—offer sustainable alternatives, particularly in arid environments like the Middle East and North Africa. Robotic cleaners achieve 15–32% efficiency gains but are limited by high costs ($10,000–$50,000/unit) and maintenance complexity (Al-Housani et al., 2019). Electrostatic systems restore up to 32% yield with minimal resource use, though high voltage requirements pose safety challenges (Said et al., 2024). Self-cleaning coatings reduce soiling by 50–70% but require durability improvements to extend lifespans beyond 1–3 years (Virtanen et al., 2023). Bio-inspired vibration-based cleaning, with a 5% efficiency loss compared to 25% for rigid panels, is promising but untested for long-term reliability (Abd-Elhady et al., 2024).

Obeidat's (2020) Preference Selection Index (PSI) approach underscores the superiority of waterless methods, assigning high scores (0.85–0.90) for sustainability and safety, while manual and water-based methods score lower (0.60–0.70) due to environmental and labor drawbacks. Emerging technologies, such as IoT-integrated sensors and machine learning (ML) models, optimize cleaning schedules, reducing costs by 25% and water use by 40% in pilot studies (Nabti et al., 2022; Olorunfemi et al., 2022). However, scalability remains a barrier, with high sensor costs ($100–500/unit) and limited data quality in diverse climates hindering widespread adoption. Multi-criteria decision-making (MCDM) frameworks, including AHP and FTOPSIS, enhance method selection but lack standardized metrics and accurate cost data, as noted by Sindhu et al. (2017) and Deb and Brahnam (2022).

Future research must prioritize durable coatings with lifespans exceeding 5 years, cost-effective automation through modular designs, and IoT-ML integration for global scalability. Bio-inspired solutions require long-term validation to ensure panel longevity, while standardized metrics, such as a "Soiling Impact Factor," could unify performance evaluation. Site-specific strategies tailored to regional dust properties and climatic conditions, supported by automated decision-support tools, are essential to maximize efficiency and economic viability. By addressing these challenges, the solar industry can enhance PV performance, reduce maintenance costs, and align with global sustainability goals, ensuring solar energy's critical role in the renewable energy landscape.

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