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Development of an Autonomous Robotic Cleaning System for Mitigating Dust-Induced Efficiency Loss in Solar Photovoltaic Panels

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Abstract

Dust accumulation on photovoltaic (PV) modules reduces incident solar radiation and consequently affects current generation, power output and energy yield. Conventional manual cleaning is repetitive, labor intensive and, when water is used, consumes a resource that may be scarce in dusty regions. Existing robotic cleaning studies demonstrate the feasibility of dry mechanical cleaning, while recent reviews emphasize the need to combine soiling monitoring, cleaning decisions and intelligent maintenance. This paper proposes an autonomous, low-cost robotic cleaning system that integrates PV performance monitoring, condition-based cleaning, motorized traversal and a soft mechanical cleaning element. The proposed system measures electrical variables before and after cleaning and uses a cleaning threshold rather than relying only on a fixed time schedule. A prototype-oriented methodology is presented for controlled dust deposition, electrical characterization, robotic cleaning and post-cleaning verification. The manuscript defines the equations, test matrix, control logic, performance indicators and economic/environmental measures required to validate the system. Unlike approaches that focus only on the cleaning mechanism, the proposed framework closes the loop from soiling/performance assessment to cleaning and verification. The work is intended for small and distributed PV installations where a simple, low-water and condition-based cleaning solution is desirable. Experimental values in the performance section are deliberately left as measurement fields/templates where laboratory or field data are required; literature-derived values are clearly identified and are not presented as measurements from the proposed prototype.

Keywords: photovoltaic soiling; dust accumulation; robotic cleaning; autonomous maintenance; solar PV efficiency; condition-based cleaning; IoT monitoring.

1. Introduction

Solar photovoltaic technology is increasingly deployed for distributed generation, rooftop electricity, utility-scale plants and autonomous energy systems. The practical energy yield of a PV module, however, is determined not only by its rated electrical characteristics but also by environmental conditions. Dust and other contaminants deposited on the front glass reduce optical transmittance and can alter the thermal and electrical operating conditions of the module. Consequently, soiling becomes an operation-and-maintenance problem rather than merely an environmental nuisance.

The magnitude of soiling is location dependent. Particle size, composition, humidity, wind, rainfall, panel inclination and the duration between cleaning events influence both the amount of deposited material and its adhesion to the surface. Yadav et al. reported measurable seasonal variation in dust deposition and soiling losses for a rooftop BAPV system in an Indian composite climate, demonstrating that a universal cleaning interval is not necessarily appropriate for every installation [10]. Recent tropical-climate work likewise shows that cleaning frequency can change performance ratio and capacity factor, while the composition of the deposited layer can determine whether dry or wet cleaning is required [15].

Cleaning therefore has two linked objectives: remove sufficient contamination to recover energy yield, and do so at a cost and environmental burden lower than the value of the recovered energy. Water-based systems can provide effective cleaning but may be undesirable in water-stressed regions. Mechanical dry-cleaning avoids water consumption, but the cleaning element must be selected carefully to avoid scratching, abrasion or repeated mechanical damage. Electrostatic and self-cleaning approaches can reduce water use but introduce additional material, electrical or installation requirements [3,4,8,11].

Robotic systems provide an opportunity to automate repetitive cleaning and reduce direct human involvement. Parrott et al. demonstrated automated robotic dry-cleaning using a silicone-rubber brush in Saudi Arabia, while Mezghani et al. developed an autonomous waterless cleaning robot using helical brushes and ultrasonic sensing [1,8]. These studies establish the technical feasibility of robotic cleaning, but there remains a useful engineering opportunity to integrate low-cost sensing, a simple mobile mechanism, condition-based activation and post-cleaning performance verification into a single prototype-oriented architecture.

The objective of this work is therefore to develop and define an autonomous robotic PV-cleaning framework in which cleaning is triggered by a measurable soiling/performance condition rather than only by a fixed calendar schedule. The specific objectives are: (i) quantify the relationship between dust loading and PV output under controlled conditions; (ii) develop a compact robotic cleaning mechanism; (iii) implement sensor-based autonomous traversal and cleaning; (iv) compare electrical output before and after cleaning; and (v) evaluate cleaning effectiveness, energy recovery, water use and maintenance implications.

The central research question is: Can a low-cost autonomous robotic cleaner maintain PV output by removing dust only when measured performance degradation justifies a cleaning cycle?

2. Literature Survey

Research on PV soiling has developed from basic observations of power loss toward detailed studies of deposition mechanisms, predictive models, monitoring systems and automated mitigation. Kazem et al. reviewed dust accumulation and cleaning methods and emphasized that the technical and economic suitability of a cleaning method depends on the installation environment [3]. Chanchangi et al. reviewed dust and PV performance in Nigeria and highlighted the need for region-specific data because dust behavior and mitigation requirements differ between locations [5].

Younis and Alhorr examined mathematical models for describing dust-soiling effects on PV performance and noted that many models are derived under particular environmental and technological conditions, limiting universal application [6]. This observation supports the use of direct measurements in a prototype: rather than assuming a globally valid dust-to-power relationship, the proposed system can establish a local calibration between a soiling indicator and electrical performance.

Monitoring is important because cleaning is most useful when it prevents economically significant energy loss. The review by Sánchez et al. describes soiling monitoring as a prerequisite for selecting mitigation strategies and discusses the strengths and limitations of different monitoring approaches [7]. Wan et al. further surveyed dust deposition mechanisms, performance degradation, mathematical modeling, cleaning methods and monitoring systems, and emphasized integrated strategies that combine monitoring, prediction and cleaning [12].

Experimental studies provide evidence for measurable output recovery after cleaning. Majeed et al. reported that at a dust density of 4.6 g/m², output power reductions were observed in both mono- and polycrystalline modules and that

their water-based cleaning system recovered most of the module performance [2]. Kazem et al. later performed controlled experiments on mono- and polycrystalline modules and different dust types, confirming that dust characteristics and cleaning approach influence the resulting performance [9]. These findings justify using multiple dust-load conditions rather than a single 'dirty versus clean' comparison.

Preventive approaches have also been investigated. Lu et al. studied self-cleaning coatings and found reductions in dust deposition together with improvements in transmittance and PV efficiency [4]. Electrostatic cleaning has been investigated as a low-water alternative; Kawamoto demonstrated equipment capable of removing dust with low power consumption, while noting that performance depends on electrode configuration, dust loading and panel inclination [17]. Such methods can be attractive for large installations, but a compact robotic approach remains appealing when retrofitting existing panels without modifying the panel surface.

Robotic cleaning represents another major branch. Parrott et al. evaluated an automated silicone-rubber brush system over a three-month field study and reported a small daily performance advantage relative to weekly-cleaned controls without measurable panel damage [8]. Mezghani et al. developed an autonomous robot for desert zones using two helical brushes and ultrasonic sensors for real-time adjustment of position, trajectory and speed [1]. These studies demonstrate that robotics can address repetitive cleaning while avoiding direct manual labor.

Recent reviews indicate a transition toward intelligent and adaptive maintenance. Parsay et al. classify mitigation into preventive methods, monitoring, active cleaning and cleaning-schedule decision making, and argue for integration among these layers [18]. The 2026 review by Chen et al. specifically examines PV-cleaning robot structures and functional modules, while recent work has also investigated machine-learning optimization of robotic cleaning schedules [19,20]. Field evidence from 2026 additionally shows that long-duration evaluation of robotic cleaning remains important because cleaning performance and potential module degradation must be assessed together [21].

Table 1 summarizes the selected literature and its relevance to the proposed research.

Ref.	**Main focus**	**Contribution relevant to this work**	**Remaining opportunity**
[1]	Autonomous robot	Waterless robotic cleaning; sensing and motion control	Low-cost integrated monitoring/verification
[2]	Cleaning experiment	Dust-related output loss and water cleaning recovery	Waterless condition-based alternative
[3]	Review	Cleaning methods and technical/economic comparison	Prototype-level closed-loop validation
[4]	Self-cleaning coating	Reduced dust deposition and improved performance	Coating-free retrofit option
[5]	Regional review	Dust-soiling mechanisms and mitigation	Local calibration required
[6]	Modeling review	Dust-to-performance model limitations	Direct measured calibration
[7]	Soiling monitoring	Monitoring needed for mitigation decisions	Simple embedded implementation
[8]	Robotic dry cleaning	Field-tested silicone brush robot	Condition-based triggering
[9]	Indoor experiment	Dust types and cleaning effects	Integrated robotic test
[10]	India rooftop study	Seasonal deposition and cleaning frequency	Automation for local conditions
[11]	Comprehensive review	Dust, cleaning and	Integrated low-cost

		sustainable solutions	prototype
[12]	Comprehensive survey	Monitoring + modeling + cleaning strategy	Closed-loop implementation
[13]	Cleaning review	Climate-dependent cleaning technologies	Decision criterion for small systems
[14]	Economic review	Dust impacts and cleaning costs	Prototype-level life-cycle comparison
[15]	Tropical field study	Cleaning frequency and tropical dust composition	Adaptive robotic cleaning

2.1 Research Gap and Proposed Contribution

The literature establishes three important facts. First, dust can produce significant and site-dependent PV losses. Second, no single cleaning technology is optimal under all climatic and operational conditions. Third, recent work increasingly points toward monitoring and adaptive cleaning rather than purely fixed schedules. The research gap addressed here is the engineering integration of these concepts into a compact system suitable for experimental validation.

The proposed contribution is not claimed to be the invention of robotic PV cleaning itself; robotic dry-cleaning has already been demonstrated. Instead, the contribution is the integration of five functions in a low-cost prototype: (1) local electrical performance sensing, (2) a condition-based cleaning decision, (3) autonomous mechanical traversal, (4) controlled dry cleaning using a soft brush, and (5) post-cleaning verification of recovered electrical output. This distinction is important for publication because it positions the work as an integrated engineering solution rather than repeating an established robotic-cleaning concept.

Figure 1 shows the proposed system architecture.

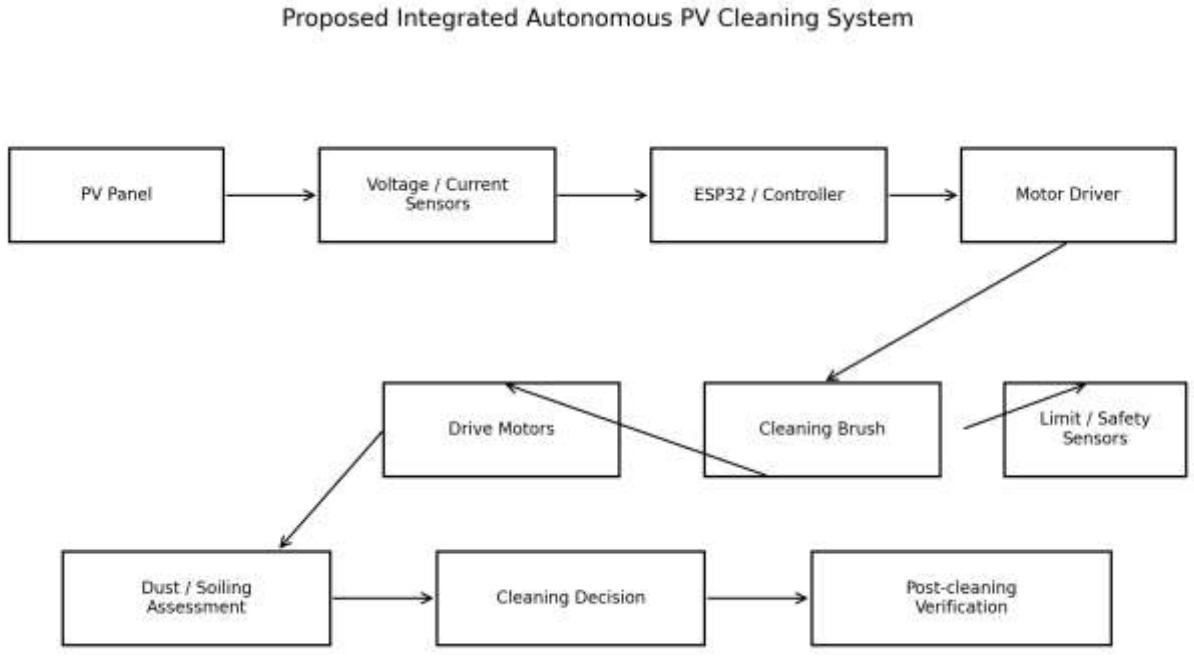
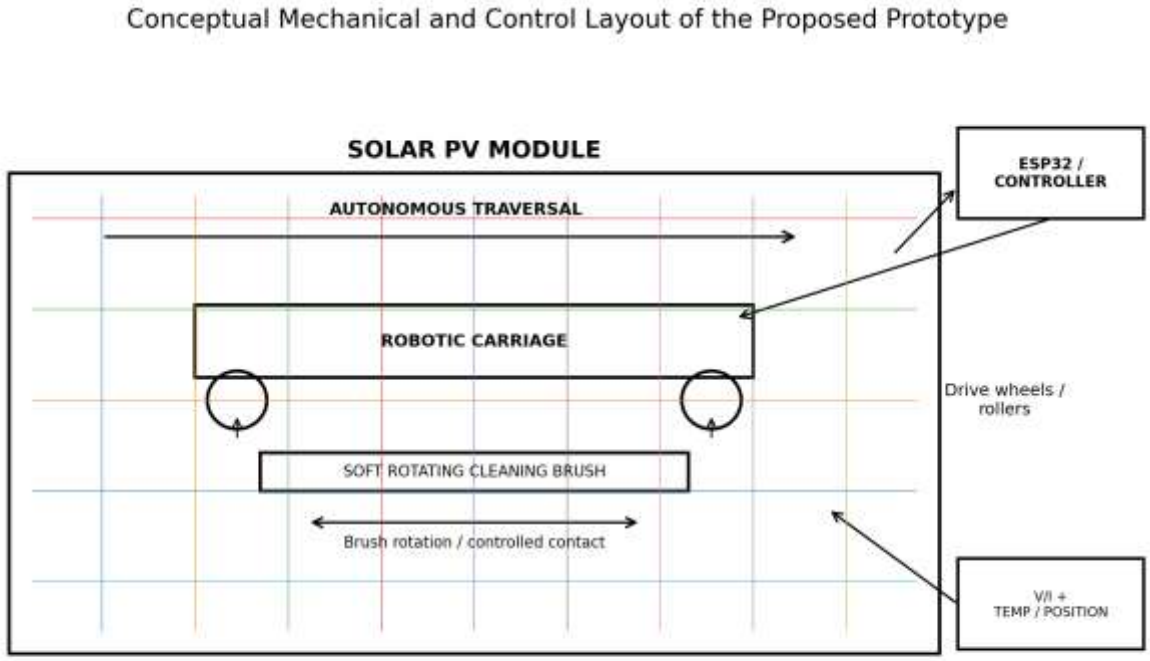


Fig. 2. Proposed integrated autonomous PV cleaning architecture.

A second contribution is the use of measured power recovery as a feedback variable. If cleaning is performed but output does not improve sufficiently, the system can flag the condition for inspection instead of repeatedly executing the same cleaning cycle. This allows the robot to act as a maintenance device and a diagnostic aid.

3. Methodology

Fig. 1. Conceptual mechanical and control layout of the proposed autonomous PV-cleaning prototype.



3.1 System Design

The proposed prototype consists of a small PV module, a mobile robotic frame, a soft cleaning brush, geared DC motors, motor drivers, a microcontroller, electrical sensors and limit/safety sensors. An ESP32-class controller is suitable for the prototype because it provides sufficient digital I/O and connectivity for data logging or IoT transmission. The mechanical structure should be lightweight so that the cleaning system does not impose excessive load on the module or create unstable motion.

The robot is designed to move along a defined path across the panel. The cleaning brush is positioned so that it makes controlled contact with the glass. A soft silicone or microfiber-type cleaning element may be selected after abrasion testing. The brush drive and traversal drive should be mechanically separated so that brush speed and robot travel speed can be adjusted independently. This allows cleaning effectiveness to be studied as a function of contact speed and brush rotation.

The design targets are: low water consumption, low auxiliary power, repeatable motion, minimal surface contact pressure, simple control, easy mounting and measurable performance recovery.

3.2 Electrical Measurement

PV voltage and current are measured immediately before and after each cleaning event. Electrical power is calculated from P=VI. To reduce errors caused by rapidly changing irradiance, measurements should be taken within a short interval or normalized using a reference irradiance measurement. Panel temperature should also be recorded because PV voltage is temperature dependent.

For controlled laboratory tests, the panel can be exposed to a stable light source or tested outdoors during a stable irradiance window. If outdoor measurements are used, the same panel orientation and measurement window should be maintained for the clean and soiled conditions. The dust loading should be measured gravimetrically where possible by applying a known mass per unit area.

3.3 Dust Preparation

A controlled dust-loading experiment should use at least four conditions: clean, low dust, medium dust and high dust. The selected dust should be documented by source and basic characteristics. Dust should be distributed uniformly

across the active glass area to improve repeatability. For outdoor validation, naturally accumulated dust should be measured separately rather than assuming laboratory dust is representative of the field environment.

3.4 Mechanical Cleaning

The cleaning cycle begins after the controller receives a cleaning command. The brush is activated first at a controlled speed, followed by traversal of the panel. The robot should move at constant or measured velocity. At the end of the stroke, the brush is stopped and the robot returns to its home position. Limit switches or position sensors should prevent over-travel. A current threshold can be used to detect abnormal mechanical resistance and stop the drive.

3.5 Control Parameters

Parameter	Suggested experimental levels	Purpose
Dust loading	0, 2, 4, 6, 8 g/m²	Relate dust to power loss
Robot speed	Low / medium / high	Study cleaning effectiveness
Brush speed	Low / medium / high	Optimize contact action
Cleaning threshold	5–15% power-loss band	Condition-based triggering
Cleaning passes	1–3	Measure recovery versus cycles
Panel temperature	Recorded continuously	Normalize electrical comparison
Irradiance	Recorded continuously	Normalize power comparison

3.6 Autonomous Decision Algorithm

A simple condition-based algorithm is preferable for the first prototype because it is transparent and experimentally verifiable. The controller periodically samples electrical and environmental variables. A baseline clean-panel power, P_{clean}, is established under comparable irradiance and temperature. The measured soiling-related power deficit is estimated as a normalized difference between baseline and current power.

$$\text{Soiling-related power loss (\%)} = [(P_{clean} - P_{soiled}) / P_{clean}] \times 100$$

When the estimated loss exceeds a predefined threshold L_{th}, the controller initiates the cleaning sequence. The threshold should not be selected arbitrarily; it can be varied experimentally to determine the point at which recovered energy justifies the auxiliary energy and maintenance cost of cleaning.

Energy consumed by the cleaning robot:

$$E_{robot} = \int V_{robot}(t)\, I_{robot}(t)\, dt$$

Net recovered energy per cycle:

$$E_{net} = E_{recovered} - E_{robot}$$

A more advanced version can replace the fixed threshold with a predictive model using irradiance, temperature, humidity, recent dust accumulation and historical power loss. However, the proposed paper deliberately begins with a transparent rule-based controller so that the mechanical and electrical contribution can be isolated before adding machine learning.

Figure 2 presents the proposed condition-based logic.

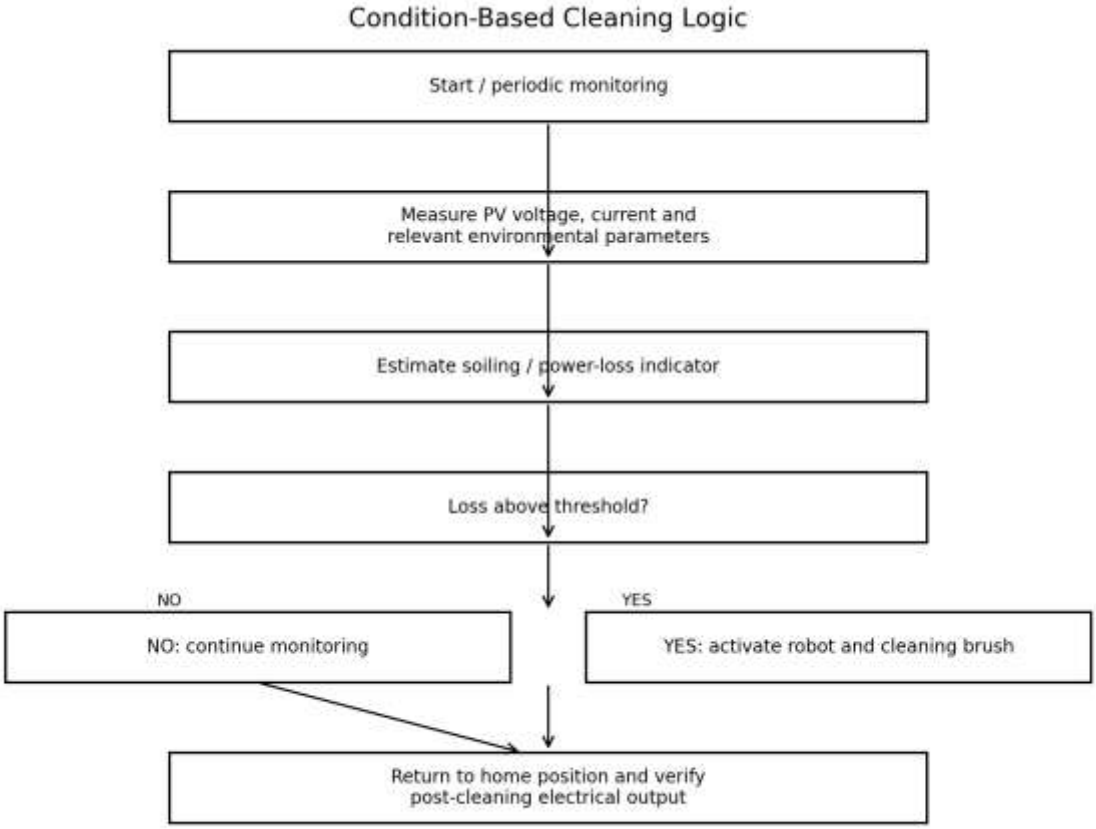


Fig. 3. Condition-based autonomous cleaning and verification flow.

3.7 Experimental Test Procedure

Each experiment should follow the same sequence: (1) clean the panel and record baseline electrical output; (2) apply a measured dust load; (3) allow the dust to settle for a defined period; (4) measure voltage, current, irradiance and temperature; (5) calculate power loss; (6) activate the robot; (7) repeat the electrical measurement; and (8) calculate cleaning effectiveness and recovered power. At least three repeated trials per condition are recommended to quantify repeatability.

The cleaning effectiveness should be evaluated using both physical and electrical measures. Physical cleaning effectiveness can be estimated from dust mass removed, while electrical effectiveness is measured from the fraction of lost power recovered. The two measures need not be identical because a small residual amount of dust may have a disproportionately small optical effect, while localized contamination can have a larger electrical effect than its mass alone suggests.

3.8 Performance Metrics

The principal performance metrics are PV power recovery, cleaning efficiency, auxiliary energy consumption, cleaning time, water consumption, repeatability and mechanical safety. These metrics are selected because a robot that removes dust but consumes excessive energy or damages the glass would not provide a practical improvement.

Power recovery ratio:

$$R_P\ (\%) = [(P_{after} - P_{before}) / (P_{clean} - P_{before})] \times 100$$

When P_{clean} is measured under the same normalized conditions, R_P approaches 100% when cleaning restores the module close to its clean baseline. If irradiance differs substantially between measurements, the raw power values should not be compared directly; normalization or an irradiance-matched comparison is required.

Cleaning effectiveness based on dust mass:

$C_E (\%) = [(m_{before} - m_{after}) / m_{before}] \times 100$

Energy recovery efficiency:

$\eta_{cycle} = E_{recovered} / E_{robot}$

For economic evaluation, the recovered energy can be multiplied by the applicable electricity value and compared with the cost of the cleaning cycle. The analysis should include robot auxiliary energy, replacement of brush elements, expected maintenance, and water consumption if a hybrid wet-cleaning option is later considered.

3.9 Mechanical Safety and Surface Protection

The cleaning brush must be tested before full operation. A simple glass witness plate or spare PV module can be used for repeated brush-pass tests. The surface should be inspected for visible scratches or haze after a specified number of cycles. Brush pressure should be kept as low as practical while still achieving repeatable dust removal. This is particularly important because repeated cleaning can introduce a second degradation mechanism even when each individual cleaning event appears harmless.

3.10 Data Acquisition and Processing

The controller records timestamp, voltage, current, calculated power, panel temperature, ambient temperature, irradiance where available, robot state, brush state and cleaning-cycle count. Data are stored locally or transmitted to an IoT dashboard. A common sampling interval such as 1–10 s can be selected for prototype experiments. Higher sampling rates are useful during motor startup and cleaning events to capture transient current consumption.

For each test condition, mean, standard deviation and coefficient of variation should be reported. A statistical comparison can be made between pre-cleaning and post-cleaning power under matched irradiance. If sufficient repeated observations are collected, analysis of variance can be used to determine whether dust level, robot speed and brush speed significantly influence recovery.

3.11 Literature-Focus Visualization

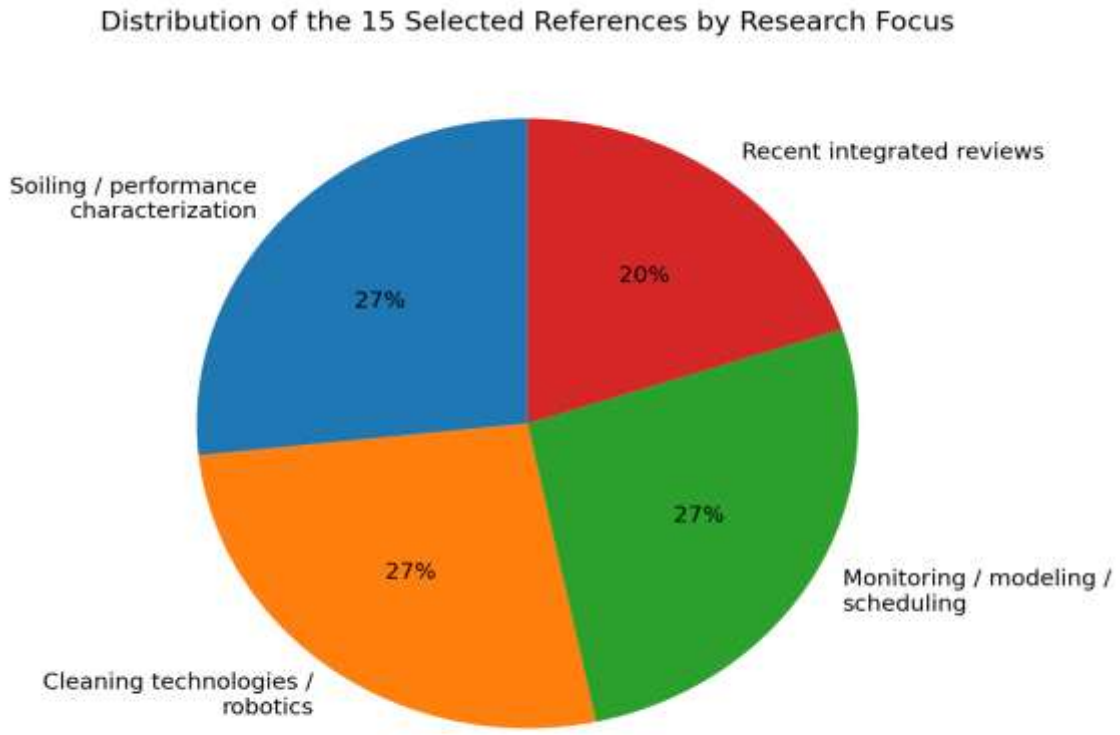


Fig. 4. Distribution of the 15 selected references by primary research focus; classification is a literature-mapping aid, not an experimental result.

3.12 Prototype Bill of Materials and Integration

A publication-ready prototype should document the exact component model, rating and quantity. The following table is a proposed architecture; actual part numbers and prices should be inserted after procurement.

Subsystem	Typical component	Function
PV source	Small mono/polycrystalline module	Energy generation and test surface
Controller	ESP32 or equivalent MCU	Sensor processing and motor control
Voltage sensing	PV voltage sensor/divider	PV operating-point measurement
Current sensing	Hall-effect current sensor	PV current measurement
Motor drive	Dual H-bridge / suitable driver	Traversal and brush motors
Drive system	Geared DC motors + wheels/rollers	Robot movement
Cleaning unit	Soft brush / silicone cleaning element	Dust removal
Position sensing	Limit switches / distance sensors	End-point and obstacle protection
Temperature	Thermistor/DS18B20-type sensor	Panel temperature correction
Irradiance	Reference sensor/pyranometer if available	Power normalization
Data logging	MicroSD / IoT dashboard	Experiment records
Power electronics	DC-DC converter / battery	Regulated robot supply

The prototype should be powered independently from the PV measurement circuit when possible. This avoids confusing robot auxiliary consumption with the PV output under test. If the PV module powers the robot directly, the measurement architecture must isolate the measurement load from the robot's consumption or clearly account for it in the energy balance.

3.13 Proposed Novelty Statement

The novelty claim should be stated conservatively: the work proposes an integrated low-cost autonomous cleaning framework that combines local PV performance sensing, condition-based activation, dry mechanical cleaning, autonomous traversal and post-cleaning verification. The system is designed for experimental comparison rather than claiming that robotic cleaning itself is new. This positioning differentiates the work from studies that focus primarily on cleaning hardware, laboratory dust characterization, or cleaning-frequency optimization as separate problems.

3.14 Experimental Design Matrix

The recommended experiment uses a factorial-style test matrix. The initial study can vary dust loading and cleaning strategy while holding other parameters as constant as possible. A later study can introduce robot speed and brush speed as independent variables.

Test ID	Dust condition	Cleaning state	Robot speed	Measured outputs
T1	Clean	No cleaning	—	V, I, P, irradiance, temperature
T2	Low	Before cleaning	—	V, I, P, irradiance, temperature
T3	Low	After one pass	Medium	V, I, P, cleaning time
T4	Medium	Before cleaning	—	V, I, P, irradiance, temperature
T5	Medium	After one pass	Medium	V, I, P, cleaning time
T6	High	Before cleaning	—	V, I, P, irradiance,

				temperature
T7	High	After one pass	Medium	V, I, P, cleaning time
T8	High	After repeated passes	Low/Medium	V, I, P, cleaning time
T9	Natural outdoor dust	Before cleaning	—	Field variables
T10	Natural outdoor dust	After autonomous cycle	Automatic	Field variables

3.15 Error Control

Major sources of experimental uncertainty include changes in solar irradiance, module temperature, dust non-uniformity, sensor calibration, brush pressure, robot trajectory and electrical load. Irradiance and temperature should therefore be recorded for every observation. Sensor calibration should be checked against reference instruments where available. The same panel should be used for paired comparisons whenever possible.

Dust distribution should be controlled using a mass-per-area method. The target dust mass should be measured before application and, when feasible, residual mass should be measured after cleaning. Robot speed should be calculated from travel distance and measured travel time rather than inferred from motor rating. Brush rotational speed should also be measured if it is treated as an experimental variable.

3.16 Practical Deployment Considerations

For rooftop deployment, the robot must be secured against sliding or falling. The prototype should initially be tested horizontally or on a safe low-height test frame. Field deployment should only follow structural and electrical safety verification. The cleaning system must not obstruct drainage, shade the module for extended periods, or interfere with electrical connectors and cables.

The proposed architecture is intentionally modular. The mechanical cleaner can be upgraded from a simple brush to a microfiber roller, silicone foam brush, air-assisted cleaner or electrostatic element. Likewise, the rule-based cleaning threshold can later be replaced with a machine-learning scheduler once sufficient site-specific data are available. This staged approach keeps the first prototype explainable while providing a pathway toward intelligent maintenance.

4. Performance Evaluation

This section defines how the proposed system should be evaluated. Because no prototype measurement dataset was supplied with the manuscript request, numerical values obtained from the literature are not presented as results of the proposed prototype. Before publication, the researcher should replace the measurement fields below with actual experimental data and statistical analysis.

4.1 Expected Experimental Relationship

The expected physical relationship is that increasing dust loading will reduce optical transmission and PV output. The exact magnitude should be measured for the selected panel, dust type, environmental condition and installation angle rather than copied from another location. Published studies show that the magnitude is highly variable. For example, Majeed et al. observed output reductions at a dust density of 4.6 g/m², while Wan et al. report a broad range of degradation values across regions and studies [2,12].

4.2 Measurement Table — To Be Completed

Dust load (g/m²)	**Irradiance (W/m²)**	**Temp. (°C)**	**P_before (W)**	**P_after (W)**	**Recovery (%)**
0	[measure]	[measure]	[measure]	[measure]	—
2	[measure]	[measure]	[measure]	[measure]	[calculate]
4	[measure]	[measure]	[measure]	[measure]	[calculate]
6	[measure]	[measure]	[measure]	[measure]	[calculate]
8	[measure]	[measure]	[measure]	[measure]	[calculate]

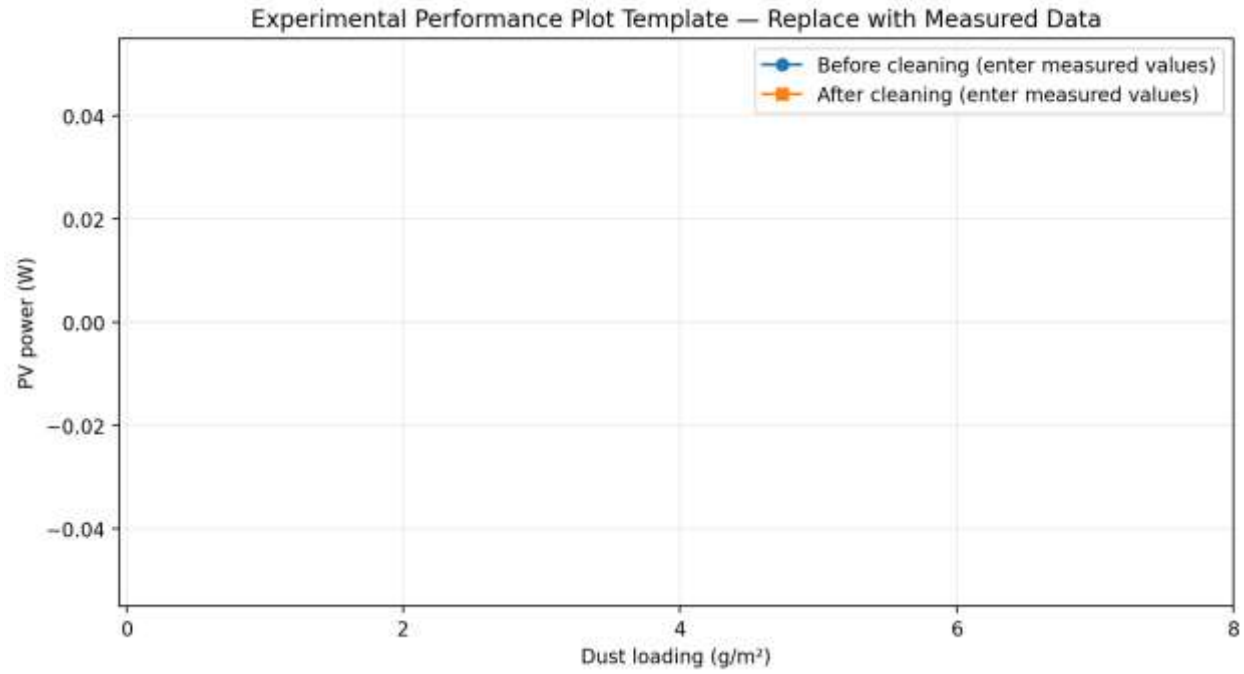


Fig. 5. Performance plot template. Replace the empty series with measured data before submission.

4.3 Literature Benchmark

Published evidence can be used as a benchmark rather than as prototype results. Parrott et al. reported approximately 0.25% per day performance improvement from the robotic dry-cleaning system during their field study, while Majeed et al. reported substantial recovery after their water-based cleaning process [2,8]. These values demonstrate feasibility but should not be used to predict the proposed prototype's performance because the module size, dust, climate, cleaning mechanism and test protocol differ.

4.4 Cleaning Effectiveness

Cleaning effectiveness should be reported at each dust level. The most informative graph is a paired comparison of P_before and P_after under normalized irradiance. A second graph should show recovery percentage against dust loading. A third should show cleaning time and robot energy consumption against cleaning passes.

Metric	Definition	Required measurement
Power loss	Difference between clean baseline and soiled output	V, I, irradiance, temperature
Power recovery	Recovered fraction after cleaning	P_before, P_after, P_clean
Cleaning efficiency	Dust removed / initial dust	Dust mass before/after
Cleaning time	Time per complete cleaning cycle	Controller timestamp
Robot energy	Auxiliary electrical energy per cycle	Robot V and I
Net energy benefit	Recovered energy minus robot energy	PV energy + robot energy
Repeatability	Variation among repeated trials	At least 3 trials/condition

4.5 Comparative Analysis with Existing Approaches

The proposed system should be compared with at least three alternatives: manual dry cleaning, fixed-interval robotic cleaning and the proposed condition-based robotic cleaning. The comparison should consider energy recovery, auxiliary energy, water consumption, cleaning time and operator involvement.

Criterion	Manual cleaning	Fixed-interval robot	Proposed condition-based robot
Human labor	High	Low	Low
Water requirement	Depends on method	Potentially zero for dry brush	Target: zero for dry cleaning
Cleaning trigger	Human decision	Calendar/time	Measured condition
PV performance feedback	Usually manual	May be absent	Included
Post-clean verification	Manual	Not always included	Included
Adaptability to site conditions	Moderate	Low–moderate	High
Prototype complexity	Low	Moderate	Moderate

This table is a design comparison, not a claim that every commercial or research system has these exact characteristics. Actual comparative testing should be performed where the paper makes quantitative claims.

4.6 Power and Energy Balance

The robot's energy requirement is a key parameter. A cleaning cycle that consumes nearly as much energy as it recovers would not be beneficial even if its physical cleaning efficiency is high. Therefore, each cycle should record motor current, controller current and operating time. The energy cost can then be compared with the additional PV energy obtained over a defined evaluation period.

Net benefit = Additional PV energy recovered − Cleaning-system energy consumption

For a daily or periodic maintenance schedule, the cumulative net energy should be calculated over the same time period as the cleaning interval. This avoids overstating the benefit of a single cleaning event.

4.7 Economic Performance

Economic evaluation should include the initial prototype cost, annual maintenance, brush replacement, electricity used by the robot and the value of recovered PV energy. For a research prototype, the goal is not to claim commercial profitability but to establish the variables required for future techno-economic optimization.

Economic parameter	Symbol	Measurement / input
Prototype capital cost	C_cap	Actual component purchase cost
Cleaning energy/cycle	E_robot	Measured Wh/cycle
Electricity value	C_e	Applicable local tariff or avoided energy value
Recovered energy/cycle	E_rec	Calculated from normalized PV output
Brush replacement interval	N_brush	Measured/estimated cycles
Annual maintenance	C_maint	Actual maintenance cost
Water use	W	Measured L/cycle; target near zero for dry cleaning
Simple payback	PBP	C_cap / annual net benefit

The proposed dry-cleaning architecture has a potential environmental advantage because it can avoid routine water use. This should be quantified rather than stated qualitatively. A water-saving claim can be calculated by comparing the proposed system's measured water consumption with the consumption of the selected conventional cleaning baseline.

4.8 Reliability and Repeatability

Reliability should be evaluated through repeated cleaning cycles. Important observations include motor stall events, missed end points, brush clogging, wheel slip, sensor errors and cleaning inconsistencies. A useful reliability metric is

successful autonomous cycles divided by total commanded cycles. The test should also record whether a cleaning cycle leaves the panel in a condition that requires manual intervention.

Surface safety should be assessed after repeated passes. Visual inspection alone is a preliminary check; where available, optical transmission, surface roughness or microscopy can provide stronger evidence. Since published robotic studies have investigated panel damage over field periods, the proposed work should treat surface protection as a primary performance requirement rather than an afterthought [8,21].

4.9 Expected Outcomes

The expected outcome is not a predetermined percentage improvement but an experimentally established operating region in which dust-induced power loss is large enough to justify cleaning and the selected brush/robot settings restore a substantial fraction of that lost power without excessive auxiliary energy. The most valuable result would therefore be a threshold map linking dust level, power loss, cleaning time and net energy recovery.

Example result statement format for the final paper: “At a dust loading of [X] g/m² and irradiance of [Y] W/m², the proposed system recovered [Z]% of the pre-cleaning power deficit after [N] cleaning pass(es), while consuming [E] Wh per cycle.”

4.10 Discussion

The literature indicates that PV soiling is strongly site dependent, which means a robot designed for a desert utility plant should not automatically be assumed optimal for a humid tropical rooftop. The 2026 Indonesian study is particularly relevant to this issue: it reported that weekly cleaning maintained the highest performance metrics, while monthly cleaning provided a closer performance level with a different maintenance burden [15]. This supports adaptive rather than universally fixed cleaning intervals.

The proposed prototype addresses this requirement by making the cleaning decision dependent on measured performance. The system does not need to know the exact physical dust mass if it can reliably identify a meaningful degradation in PV output under comparable irradiance and temperature. This reduces the need for expensive dust-imaging hardware during the first prototype stage. A future version can add optical dust sensing or camera-based detection once sufficient calibration data are available.

A second advantage is the closed-loop verification step. Many cleaning mechanisms are evaluated mainly by how much dust they remove. For energy applications, however, the relevant output is recovered electrical energy. The proposed system therefore measures PV performance after cleaning. If the recovered output is insufficient, the system can identify possible problems such as incomplete cleaning, persistent contaminants, sensor error, module degradation or abnormal operating conditions.

A third contribution is the possibility of combining robotic cleaning with predictive maintenance. Once a sufficiently large dataset is collected, the controller could estimate future power loss from weather, historical cleaning cycles and environmental variables. Recent 2026 work has already begun exploring machine-learning optimization of robotic cleaning schedules, demonstrating that the field is moving toward data-driven maintenance [20]. The proposed prototype can serve as the data-generation platform for such future work.

4.11 Limitations

The first-stage system has several limitations. A brush-based mechanism may not remove strongly adhered organic-mineral deposits, and wet cleaning may still be necessary under some tropical conditions. The prototype may also be limited to a single panel size and geometry. Outdoor measurements are affected by changing irradiance, wind and temperature, making normalization essential. The cleaning threshold requires site-specific calibration, and a short experimental period cannot establish long-term module degradation or commercial reliability.

These limitations do not invalidate the prototype; rather, they define the next experimental stages. Future work should include longer field trials, multiple panel technologies, naturally accumulated dust, seasonal variation, brush-wear analysis and comparison with electrostatic or air-assisted cleaning. Long-term robotic field studies are especially

important because cleaning performance must be considered together with any cumulative mechanical effects on module surfaces [21].

5. Conclusion

This paper proposed an autonomous robotic cleaning framework to mitigate dust-induced efficiency loss in solar photovoltaic panels. The research problem was formulated around the mismatch between continuous dust accumulation and conventional fixed or manual maintenance. A low-cost integrated architecture was developed conceptually around PV electrical monitoring, a microcontroller, motorized traversal, a soft dry-cleaning element, safety/position sensors and post-cleaning performance verification.

The literature survey shows that dust accumulation can significantly reduce PV performance, that cleaning effectiveness is dependent on environmental conditions, and that robotic dry-cleaning has already demonstrated technical feasibility. The main contribution proposed in this work is therefore not robotic cleaning alone, but the integration of condition-based activation and post-cleaning electrical verification with a compact robotic mechanism. This creates a closed maintenance loop: measure performance → identify significant degradation → clean automatically → verify recovery → continue monitoring.

The methodology defines controlled dust-loading experiments, repeated cleaning trials, electrical and environmental measurements, power-loss and recovery calculations, auxiliary-energy accounting, safety checks and economic evaluation. The performance section deliberately provides a measurement framework rather than fabricated prototype results. Once experimental data are collected, the manuscript can quantify the dust threshold at which cleaning becomes beneficial, the optimum robot/brush operating parameters, the net energy benefit and the repeatability of autonomous operation.

Compared with prior literature that separately investigates dust characterization, cleaning mechanisms, monitoring or cleaning schedules, the proposed approach aims to combine these functions in one low-cost experimental platform. The system can subsequently be extended with optical dust sensing, IoT dashboards and machine-learning scheduling. Such extensions would move the system from simple automation toward predictive, site-adaptive PV maintenance.

In conclusion, the proposed autonomous cleaning system provides a practical research pathway for reducing dust-related PV energy losses while minimizing routine manual intervention and water consumption. The final publication should include the authors' actual prototype dimensions, component specifications, measured data, statistical analysis, photographs and experimental results in place of the indicated measurement fields. These additions will be essential before submitting the work as an original experimental research article.

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