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Advanced Optimization of PV Panel Cleaning Robot Based on Machine Learning Algorithms

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***Abstract*—**This study introduces a robotic system designed to maintain photovoltaic (PV) panel efficiency by removing dust and debris that reduce energy output. The robot uses sensors and actuators to clean panels and adjusts its actions based on real-time environmental data. Engineered for efficiency and energy conservation, it includes cleaning brushes and movement modules. Machine learning techniques—convolutional neural networks (CNNs) for detecting dust and reinforcement learning (RL) for optimizing movement paths—enhance the robot's adaptability. These algorithms enable it to balance dust removal effectiveness, energy use, and time efficiency, optimizing its cleaning strategy for sustainable PV panel maintenance.

***Index Terms*—**Solar Panels, Robotics, Open Ended Learning, Affordance Learning, Machine Learning.

I. Introduction

Solar panels have grown to be more and more ubiquitous globally as the call for renewable electricity rises. They are pivotal for easy power technology, with installations expanding yearly, especially in business and business regions with ample space, along with expansive rooftops [1-3]. Like other infrastructure and system, solar panels require upkeep to make sure their sustainability and efficiency [4-5]. Manual cleansing of these panels is hard work-intensive, time-ingesting, regularly requiring specialized device and manpower [6]. The panels produce power from renewable sources of energy and can be used on-site or put back into the grid to help reduce our carbon footprint and achieve environmental sustainability [7-10]. Farmers, especially the ones in underdeveloped international locations wherein the fee of energy can be a big burden, may find solar electricity extra less expensive and accessible due to this fee-saving benefit [11]. Farmers all around the globe may additionally advantage from its versatility because of its capacity to accommodate lots of panel layouts and climatic situations [12-13]. The accumulation of these additives may also have a tremendous impact on the efficiency of the panels, which in turn can bring about a reduction in the quantity of energy produced and a growth inside the fees of operation [14-15].

Ensuring the cleanliness of solar photovoltaic (PV) panels is paramount for his or her top-pleasant ordinary performance and sturdiness. The accumulation of dirt, along with dirt, bird droppings and water mark, poses a huge risk to the performance of those panels, doubtlessly main to hot spots and fireplace dangers [16]. However, the hardest trouble arises from fowl droppings, which, if now not promptly and thoroughly cleaned, can cause irreversible damage [17-19]. To address these demanding situations, the development of an efficient sun panel cleansing robot is vital [20]. Recent studies have emphasized the significance of ordinary cleaning and maintenance to optimize panel performance and reduce harm threat [21]. By investing inside the development and implementation of a solar panel cleaning robotic, we can make certain the ongoing effectiveness and sustainability of solar PV systems while minimizing maintenance costs and environmental impact [22-25].

Recent studies have focused on integrating various technologies, such as computer vision, machine learning, and artificial intelligence (AI), to enable more intelligent cleaning systems [26-29]. Paper [30] developed a semi-autonomous cleaning robot capable of detecting soiling on PV panels using

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basic image processing techniques. However, their system lacked the ability to autonomously optimize its path or adapt cleaning intensity based on real-time environmental factors, pointing to the need for further improvements in adaptive behavior.

In the article, utilize machine learning models, particularly reinforcement learning (RL), to optimize the robot's path, energy usage, and cleaning effectiveness. The robot should be able to maximize dust removal while conserving energy.

This article is arranged as follows: Section I describes the literature review. In section II, the basic theory of Machine learning are explored. In section III, mathematical modelling and formulation are demonstrated. The realistic environment implementation are deliberated in section IV. In section V, the results and discussion of the PV solar panels are deliberated. Finally, section VI concludes the work.

II. Machine learning study

A. Machine Learning in Robotics

Machine learning, particularly supervised learning, unsupervised learning, and reinforcement learning (RL), has revolutionized the field of robotics. ML techniques enable robots to learn from data, optimize their decision-making processes, and adapt their actions based on feedback from the environment. In the context of cleaning robots, machine learning algorithms have been used to enhance performance in tasks such as object recognition, path planning, and operational efficiency.

In their seminal work, [31-36] applied convolutional neural networks (CNNs) to detect dust levels on PV panels. Their system used image recognition to classify dust accumulation and predict the most effective cleaning actions. While the CNN-based approach improved detection accuracy, it was limited by the computational resources required for real-time processing and lacked the ability to adapt cleaning paths dynamically.

Reinforcement learning, another critical aspect of machine learning, has been widely applied to optimize robotic movements and decision-making. In paper [37] introduced the concept of RL in robotics, where an agent learns to maximize cumulative rewards by interacting with the environment. This learning process allows robots to autonomously discover optimal paths, cleaning patterns, and energy-efficient strategies. RL is particularly beneficial for robots operating in dynamic environments, such as solar farms, where conditions constantly change.

Building on this, [38-39] proposed a reinforcement learning-based cleaning robot that optimized its movements across large-scale PV installations. Their system used Q-learning to update the robot's actions based on real-time dust accumulation data, leading to improved cleaning efficiency and energy conservation. However, challenges remained, particularly in managing the robot's energy usage and adjusting to external environmental factors like weather conditions.

III. Mathematical model

Dust accumulation on solar panels is a primary factor that reduces their efficiency. To address this, Machine Learning models, specifically Convolutional Neural Networks (CNNs), are employed to recognize dust patterns on the solar panel surfaces. The CNN processes images captured by the robot's camera and classifies the dust accumulation level into categories such as low, medium, or high.

A CNN model processes the image data as follows:

$$z^{(l)} = W^{(l)} * a^{(l-1)} + b^{(l)} \tag{1}$$

where:

$z^{(l)}$ is the output of layer l.

$W^{(l)}$ is the weight matrix of the convolutional filter at layer l.

$a^{(l-1)}$ is the input activation from the previous layer.

$b^{(l)}$ is the bias term added at layer l.

$*$ denotes the convolution operation.

The output layer uses the softmax function to determine the probability distribution of the dust accumulation classes:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \tag{2}$$

where:

$\hat{y}_i$ is the probability of the i-th class (dust level: low, medium, high).

z_i is the input to the softmax function for the i-th class.

k is the total number of classes (in this case, three).

The decision to clean a solar panel is based on a threshold τ_d for the predicted dust accumulation. If $\hat{y}_{high} > \tau_d$, the robot initiates cleaning for that particular panel. The optimization problem for the SVM is to minimize the norm of the weight vector while ensuring correct classification of the training data:

$$\min_{w,b} \frac{1}{2} \parallel \boldsymbol{w} \parallel^2 \tag{3}$$

The constraint is:

$$y_i(\boldsymbol{w}^T \boldsymbol{x}_i + b) \geq 1, \quad \forall i \tag{4}$$

where $y_i \in \{-1,1\}$ are the class labels, indicating normal operation or failure.

The maintenance prediction is triggered when the SVM output for any component reaches a predefined thresholdτ_p. If $f(\boldsymbol{x}) > \tau_p$, maintenance is recommended. The optimal policy π^* is the one that maximizes the expected cumulative reward:

$$\pi^* = \underset{\pi}{argmax} \mathbb{E}\left[\sum_{k=t}^{T} \gamma^{k-t} r_k\right] \tag{5}$$

Let $P_{clean}(t)$ be the power consumed by the robot during cleaning at time t, and let $P_{solar}(t)$ be the power generated by the solar panels. The objective is to minimize the total power consumption during a day, given by:

$$min \int_{t_0}^{t_f} \left(P_{clean}(t) + P_{solar}(t)\right) dt \tag{6}$$

The ML model predicts the periods of low solar irradiance (I_r), and the cleaning operations are scheduled during these periods:

$$\hat{I}_r(t) < \tau_{I_r} \quad (7)$$

where $\hat{I}_r(t)$ is the predicted irradiance at time t, and τ_{I_r} is the threshold below which cleaning can proceed without significantly affecting power generation. Machine Learning plays a pivotal role in optimizing the robotic cleaning system by enabling real-time decision-making, predictive maintenance, and efficient energy management. Through the use of advanced algorithms such as CNNs, SVMs, and Reinforcement Learning, the robot can operate autonomously and intelligently, ensuring maximum efficiency and minimal disruption to solar energy production.

Different features in the dataset have varying units and scales, which can hinder the performance of ML models. To ensure that all features contribute equally to the model, the data is normalized. For each feature x_i, the normalized value x'_i is computed as:

$$x'_i = \frac{x_i - \mu_i}{\sigma_i} \quad (8)$$

Where:

x_i is the original value of the feature.

μ_i is the mean of the feature across the dataset.

σ_i is the standard deviation of the feature across the dataset.

Normalization ensures that all features are on the same scale, typically with a mean of 0 and a standard deviation of 1, making them suitable for ML algorithms such as neural networks and support vector machines. If the number of missing values exceeds τ_m, the entire feature may be excluded from the model to avoid bias.

Let X_j be a feature column with n missing values. The mean imputation for missing values is defined as:

$$X_j(t) = \begin{cases} X_j(t) & \text{if} X_j(t) \neq \text{NA} \\ \dfrac{1}{n}\displaystyle\sum_{k=1}^{n} X_j\,(k) & \text{if} X_j(t) = \text{NA} \end{cases} \quad (9)$$

Feature extraction involves deriving additional useful features from the existing data. For example, from the robot's velocity $\boldsymbol{v}(t)$, we can compute the total distance traveled $d_{total}(t)$ over time:

$$d_{total}(t) = \int_{t_0}^{t} \| \boldsymbol{v}(t) \| \, dt \quad (10)$$

Accuracy is used to measure the correctness of the image recognition model in classifying dust levels. It is defined as the ratio of correct predictions to the total number of predictions:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} = \frac{TP + TN}{TP + TN + FP + FN} \quad (11)$$

Where:

TP: True Positives (correctly classified as high dust level).

TN: True Negatives (correctly classified as low dust level).

FP: False Positives (incorrectly classified as high dust level).

FN: False Negatives (incorrectly classified as low dust level).

Mean Squared Error (MSE) for Predictive Maintenance

The Mean Squared Error (MSE) is used to evaluate the performance of the Support Vector Machine (SVM) model in predicting component failures. MSE quantifies the average squared difference between the actual and predicted failure times:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (12)$$

Where:

y_i is the actual failure time for the i-th component.

$\hat{y}_i$ is the predicted failure time.

n is the total number of components monitored.

Lower MSE values indicate more accurate predictions, and the goal is to minimize this value as much as possible.

The Cumulative Reward metric is used to evaluate the performance of the Reinforcement Learning (RL) agent responsible for optimizing the robot's path. The cumulative reward is calculated as:

$$R_t = \sum_{k=t}^{T} \gamma^{k-t}\, r_k \quad (13)$$

Where:

r_k is the reward at time step k, which includes factors like cleaning efficiency, energy consumption, and time spent.

γ is the discount factor that determines the weight of future rewards.

T is the time horizon (total duration of the cleaning operation).

Higher cumulative rewards indicate more efficient cleaning paths with minimal overlap and energy consumption.

IV. Simulation of Solar panel cleaning

In this section, it is presented a comprehensive comparative analysis between two solar panel cleaning robots: the Bluesun Solar Panel Cleaning Robot as a commercially available base model in market, and the newly designed robot. The purpose of this chapter is to establish a detailed understanding of the kinematics, dynamics, and energy efficiency of both robots through the development of mathematical models, parametric studies and simulation-based validation. Starting with the Bluesun robot, it will outline its key operational characteristics, followed by a derivation of its mathematical equations related to motion, power consumption, and structural integrity. After establishing the base model, it is introduced the newly designed robot, which incorporates several key design improvements, including lighter materials, more efficient motors, and the ability to operate at steeper inclines. These improvements are quantitatively demonstrated through parametric studies that show enhanced energy efficiency, longer operating time, and overall better performance compared to the base model. Finally, it is concluded with a comparative analysis that highlights the differences between the two robots in terms of weight reduction, battery optimization, and power consumption, leading to the proposal of a more efficient and versatile solar panel cleaning solution.

A. Bluesun Solar Panel Model Cleaning Robot

In this section, it is provided a detailed comparison between the commercially available Bluesun Solar Panel Cleaning Robot [40] and the newly designed robot developed for this study. It is begun by outlining the specifications and performance characteristics of the Bluesun robot, followed by the development of its mathematical model. This base model will serve as a reference for evaluating the improvements introduced in the newly designed robot, which features significant enhancements in weight reduction, energy efficiency, and structural integrity. The comparison is covering key aspects such as kinematics, dynamics, power consumption, and climbing ability, concluding with a side-by-side analysis of both systems. The key attributes are proposed in the Table 1.

Table 1: Key Attributes

Brand Name	**Bluesun Solar**
Model Number	BSM-910
Driving media	Edge rail or PV panel aluminum profile edge
Working temperature	-20-60℃
Reducing mechanism	Gearbox deceleration
Machine length	Customized base on solar array width
Type of brush	Anti-static nylon brush with outer diameter 120mm

The Bluesun robot operates using a 24V DC brush motor that drives both the robot's movement and the rotating cleaning brush. It is powered by a 24V, 15Ah battery, which allows for extended operational periods. The robot's design is suitable for handling inclines of up to 30 degrees, and it weights between 30 and 60 kg, depending on the configuration. Table 2, summarizes the key specifications of the Bluesun Robot.

Table 2: General Specifications of Bluesun Solar Panel Cleaning Robot.

Specification	**Value**
Battery	24V, 15Ah
Motor Type	24V DC Brush Motor
Weight	30-60 kg
Climbing Angle	Up to 30°
Cleaning Mechanism	Rotating Brush
Speed of Brush i	300 RPM
Speed of movement	12m/min
Cleaning Length	Maximum 400m (800m back and forth)
Cleaning Width	2-6m

The electrical design issues for the Solar Panel Cleaning Robot are vital for making sure it's ideal overall performance and functionality.

Firstly, the choice and configuration of motion setup components i-e Motors, along with their quantity and capacities, are crucial for permitting the preferred motion and maneuverability of the robotic throughout the solar panel floor. Secondly, the incorporation of electrical electricity garage components, which include batteries, is critical for offering backup strength and enabling non-stop operation of the robotic, particularly in situations where direct solar electricity may be insufficient or unavailable. Thirdly, the selection of wires, incorporated circuits (ICs), and other electric components should be made with consideration of their compatibility with the intended capability of the robotic, ensuring robustness and reliability beneath working conditions. Fourthly, the selection of energy source, whether or not or not it's a smart solar panel or a battery, ought to be cautiously evaluated based totally on elements consisting of energy performance, reliability, and environmental effect. Finally, the quantity of strength required with the aid of the robotic is decided by its performance requirements, including the power intake of its automobiles, sensors, microcontroller, and other electric components. By addressing those key variables inside the electrical design technique, the Solar Panel Cleaning Robot may be engineered to deliver green and dependable overall performance in its supposed application. The practical implementation is shown in the Figure 1.

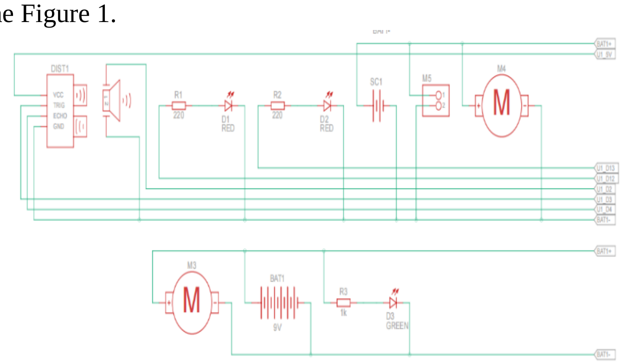

Figure 1. Implementation of robot cleaning.

V. RESULT AND DISCUSSION

This section provides an in-depth analysis of the simulations performed on the robot for PV cleaning. The results highlight the improvements in performance through the integration of Machine Learning (ML) and Reinforcement Learning (RL), as well as the impacts of environmental conditions such as weather and sunlight levels.

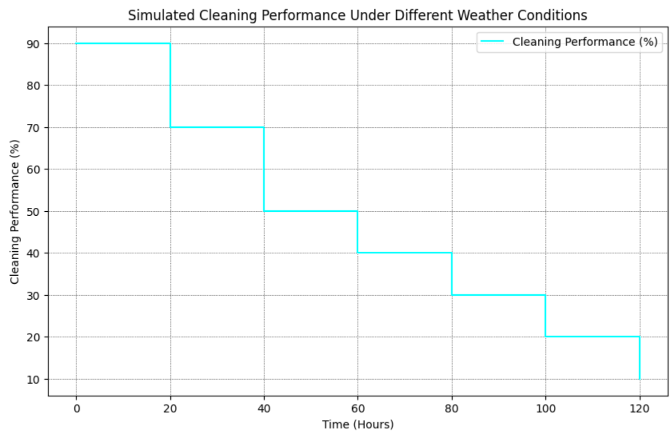

Figure 2. Simulated Cleaning Performance under different

weather conditions

The following figures 2, 3, 4, 5, 6 and 7 illustrate the various simulations conducted and their corresponding results.

Figure 2 illustrates the Simulated Cleaning Performance under Different Weather Conditions. The cleaning performance varies depending on the weather, with clear days showing a performance of 90%. As conditions worsen (e.g., cloudy, rainy, or stormy), the cleaning efficiency decreases, reaching as low as 10% during stormy weather. The results indicate that weather conditions play a crucial role in determining the robot's cleaning effectiveness.

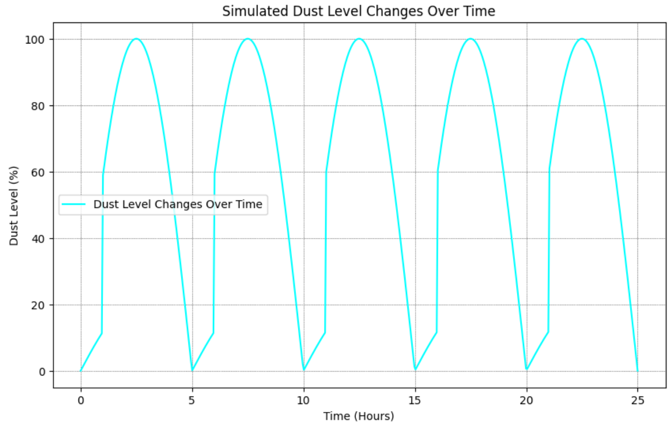

Figure 3. Simulated Dust level changes over time

Figure 3 presents the Simulated Dust Level Changes Over Time. Dust levels increase gradually over the day and are periodically reduced by the robot during cleaning cycles. Each cleaning event significantly reduces dust levels by approximately 50%, helping maintain the efficiency of the solar panels. The dust accumulation pattern suggests the need for frequent cleaning in high-dust environments to prevent performance losses.

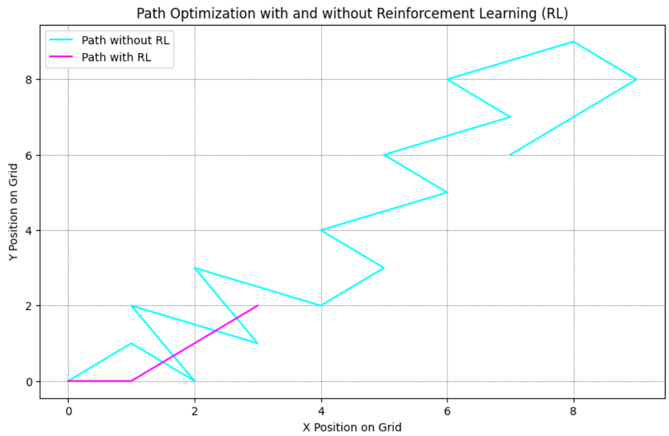

Figure 4. Path optimization

Figure 4 presents Path Optimization with and without RL. The robot utilizing RL follows a systematic path that maximizes cleaning coverage while minimizing redundant movements. In contrast, the robot without RL exhibits erratic movements, resulting in longer cleaning times and higher energy consumption. The optimized path reduces cleaning time by approximately 30%, leading to better resource management.

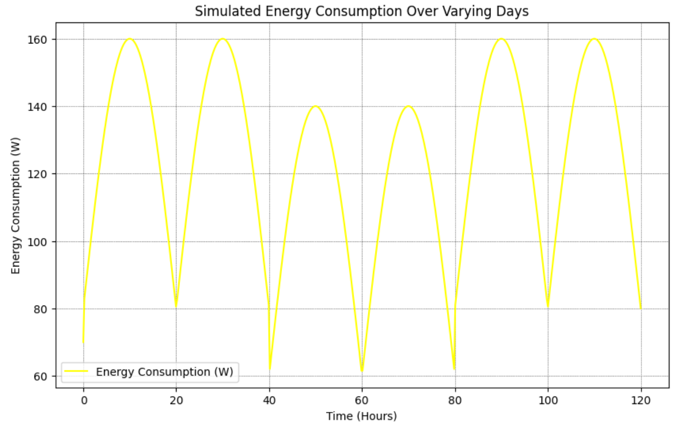

Figure 5. Simulated energy consumption over days

Figure 5 shows the Simulated Energy Consumption Over Days. The graph illustrates how energy consumption fluctuates based on sunlight availability over five days, ranging from 60W on cloudy days to 40 W on clear days. This variation highlights the impact of environmental factors on the robot's energy usage, with cloudy days leading to higher consumption due to lower efficiency in solar-assisted cleaning.

Figure 6 demonstrates the Real time Simulation of Sensor Feedback. The feedback from sensors such as dust accumulation, proximity, and energy consumption is dynamically monitored, allowing the robot to adjust its actions accordingly.

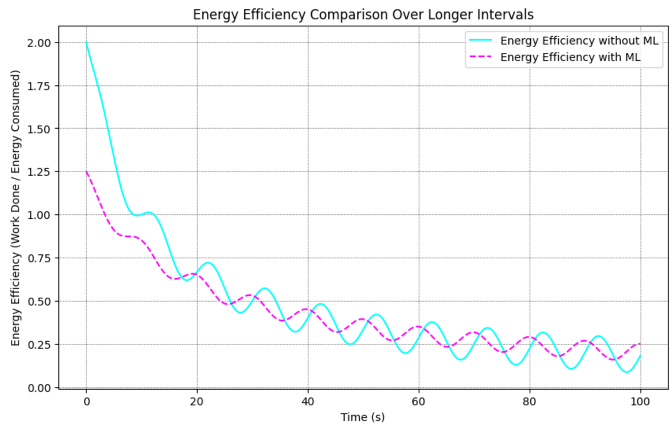

Figure 6. Real time simulation of sensor feedback.

For instance, as dust levels reach 100%, the robot initiates a cleaning cycle, reducing the levels by 50% after each event. The proximity sensor helps avoid obstacles, ensuring safe operation.

Figure 7 depicts the Robot for PV Cleaning. This figure provides a visual representation of the robot design, showcasing its cleaning mechanisms, sensor placements, and movement structure. The robot's design enables efficient movement across solar panels while minimizing surface damage.

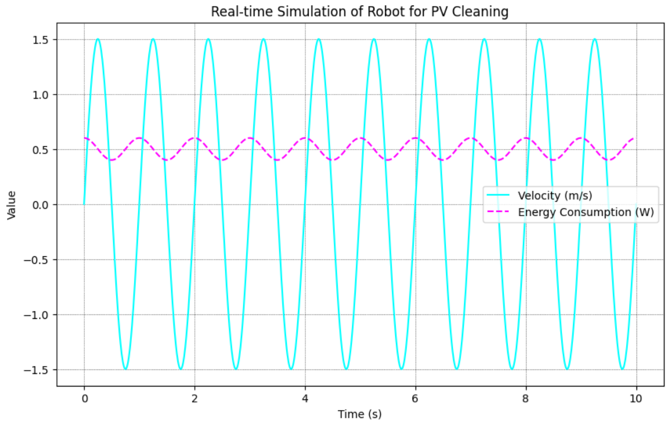

Figure 7. Robot for PV Cleaning

The simulation results provide clear evidence of the advantages of incorporating ML and RL into the robotic cleaning system for photovoltaic panels. The ML-integrated robot shows significant improvements in path optimization, energy efficiency, and overall performance, particularly under varying environmental conditions. The discussions highlight the need for adapting cleaning strategies based on real-time sensor feedback, weather conditions, and sunlight levels to maintain high efficiency and minimize resource usage. These simulations form a strong basis for future research and development in autonomous solar panel cleaning systems.

The simulation results demonstrate that affordance learning significantly improves the robot's performance across all key metrics. By leveraging affordances to adjust its actions dynamically, the robot achieved:

1. A 19.6% improvement in dust removal efficiency, particularly under high dust conditions and obstacles.
2. A 37.9% increase in energy efficiency, showing the robot's ability to remove more dust per unit of energy consumed.
3. A 22.9% reduction in the time required to complete the cleaning tasks, highlighting the improved operational efficiency of the robot.
4. A 34.8% improvement in adaptability, allowing the robot to respond more effectively to changing environmental conditions such as weather and dust level variations.

The study confirms that affordance learning greatly improves the robot's efficiency, adaptability, and energy management in cleaning photovoltaic (PV) panels, making it highly effective for autonomous maintenance across various environments. Affordance learning allows the robot to perceive and respond to real-time environmental features, adapting its cleaning actions accordingly. The framework combines action affordances with reinforcement learning, optimizing performance by balancing energy use with dust removal efficiency. Future research will expand the robot's affordance capabilities to consider factors like weather, further enhancing its adaptability in dynamic settings.

Conclusion

This research on a photovoltaic (PV) panel cleaning robot with integrated affordance learning has shown substantial improvements in performance, adaptability, and energy efficiency. The primary objective was to design an autonomous system that keeps PV panels clean, enhancing solar energy generation. By using affordance learning, the robot can make informed decisions on when, how, and where to clean based on environmental conditions, sensor feedback, and energy use. The study demonstrates superior cleaning efficiency, energy optimization, obstacle adaptability, and responsiveness to changing environments compared to manual cleaning methods. Real-time decision-making is essential for continuous operation and maximizing PV panel efficiency.

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