



## Environmental Impact on Solar PV Panel : Degradation and Economic Analysis

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**Abstract:-** With global photovoltaic (PV) capacity surpassing 2 terawatts (TW), solar energy has emerged as the most cost-effective power source in many regions. However, ensuring long-term reliability and performance remains a critical challenge, particularly due to module degradation influenced by environmental factors. This study investigates the degradation behavior of a 10-panel PV array over a three-year period using high-resolution environmental and electrical datasets. A multistep methodology comprising data preprocessing, power normalization to standard test conditions (STC), and annual aggregation was applied to assess performance metrics. The degradation rate was estimated using both linear regression and a multivariate model incorporating environmental variables such as relative humidity, ambient temperature, wind speed, global irradiance, and albedo. Results indicate an annual degradation rate consistent with literature values for polycrystalline silicon modules (0.5–1% per year), with temperature and humidity emerging as key accelerators of performance decline. The multivariate model demonstrated strong predictive accuracy, closely matching actual degradation trends. These findings highlight the significant impact of environmental stressors on PV system performance and underscore the importance of site-specific analysis for accurate forecasting. The economic analysis also emphasizes how degradation, discount rate, and system lifetime strongly affect the economic and environmental performance of grid-connected PV systems.

**Keywords:** PV panel degradation, environmental factors, degradation rate, Economic Analysis.

### 1. Introduction

The global photovoltaic (PV) capacity has surpassed 2 terawatts (TW) [1]. This rapid expansion has led to substantial cost reductions, positioning solar energy as the most affordable power source in many regions. The 2 TW capacity is equivalent to the combined installed electricity capacity of India, the United States, and the United Kingdom, and could theoretically



power approximately one billion homes, assuming a 20% capacity factor and average consumption of 3.5 MWh per year [2]. The environmental benefits of solar energy, primarily stemming from the displacement of fossil fuel-based electricity generation, are intrinsically linked to the lifespan and performance of PV systems. Studies have shown that decreased PV panel efficiency due to degradation can lead to an increased lifecycle carbon footprint, potentially undermining the intended environmental gains. Furthermore, the economic viability of solar projects is heavily dependent on sustained energy production, with degradation directly impacting the levelized cost of energy (LCOE) and overall investment returns [3],[4],[5]. Therefore, a comprehensive understanding of the factors driving PV panel degradation, along with a rigorous economic assessment, is essential for optimizing system design, operation, and maintenance strategies.

As the demand for clean and sustainable energy continues to grow, ensuring the long-term reliability and durability of PV systems has become a critical area of research. The degradation rate of PV modules plays a vital role in determining the efficiency, reliability, and economic feasibility of solar energy systems. The mitigation of these degradation rates is essential for optimizing the lifespan and performance of PV installations [6],[7]. Multivariate linear regression is used in this study because it offers a more realistic and complete analysis. It can model how multiple variables simultaneously affect an outcome, unlike simpler models that only consider one factor. This approach provides a better fit for the data, giving a more accurate picture by controlling for confounding variables [8].

This paper delves into the environmental impact of solar PV panel degradation, combining detailed analysis of degradation mechanisms with a comprehensive economic evaluation. In this study, the quantification of the effects of key environmental factors on degradation rates and the assessment of the resulting economic consequences, can help to provide stakeholders with the knowledge needed to make informed decisions that balance environmental sustainability and economic viability in solar energy investments. We explore the current state of research on degradation and its impact and will propose suitable strategies for maximizing the performance and financial returns of this form of renewable energy.

## 2. METHODOLOGY

This study estimates the degradation of a 10-panel photovoltaic (PV) array using 12-month datasets from different years. The available data includes timestamp, radiation components (direct, normal, horizontal, global), DC voltage, DC current, ambient temperature, wind speed and albedo.

### A. Data Preprocessing

Data preprocessing is a crucial step in ensuring accurate and reliable analysis of photovoltaic (PV) panel performance. The first step involves calculating the output of each individual panel by dividing the total power generated by the PV array by the number of panels which are ten in our case. This provides insight into the contribution of each panel to the overall energy production. Next, the dataset must be cleaned to remove any missing values or faulty readings,



which may result from sensor errors or external environmental conditions. Eliminating these anomalies is essential to prevent skewed results and ensure analytical accuracy. Finally, all timestamps must be checked for consistency and correct formatting. Uniform timestamps are vital for accurate time-based analysis, enabling the detection of performance trends and patterns. By following these preprocessing steps, the dataset becomes well-structured and reliable, laying the groundwork for a comprehensive assessment of PV panel performance over time.

- **Calculation of Metrics Per Timestamp**

For each data point, we calculate the DC power as follow:

$$P_{dc} = V_{dc} * I_{dc} \quad (1)$$

The power must be normalized to Standard Test Condition (STC):

$$P_{norm} = (P_{dc} / G_{global}) * 1000 \quad (2)$$

Make the power correction according to the temperature using the following relationship:

$$P_{corrected} = P_{norm} + \delta(T_{mod} - 25) \quad (3)$$

Estimate the temperature of the module ( if unavailable) by the following relationship:

$$T_{mod} = T_{ambient} + ((NOCT - 20) / 800) * G_{global} \quad (4)$$

Where the nominal operating cell temperature (NOCT) is defined as the solar panel temperature based on four main standard reference environments: Irradiation on the solar panel is equal to 800W/m<sup>2</sup>, the wind velocity is of 1 m/s and the air temperature is equal to 20°C.  $G_{global}$  is the global irradiance,  $T_{mod}$  is the temperature of the module.

## B. Annual Aggergation

The annual aggregation process begins by filtering the dataset by calendar year, followed by computing either monthly or daily averages, as required. To ensure consistency and comparability of performance metrics, data is further refined to include only clear-sky or near-standard test condition (STC) days, defined as periods when solar irradiance (G) exceeds 700 W/m<sup>2</sup>. Subsequently, the mean or median of the normalized power output per panel is calculated to represent typical performance under the selected irradiance conditions. Finally, the annual mean or median normalized power values are stored for each individual panel, facilitating longitudinal performance analysis and comparison across years.

## C. Estimation of Degradation Rate

The degradation rate of each PV array is estimated from the change in the annual average Performance Ratio (PR) converted to a PR at a temperature of 25<sup>0</sup>C ( $PR_{T=25}$ ) as defined by STC. The correction equation is given by:

$$PR_{STC} = PR * \frac{1}{1 + \delta(T - T_{STC})} * SF \quad (5)$$

Where the Performance Ratio (PR) is given by



$$PR = \frac{P_{max}(end)}{P_{max}(start)} / \frac{G}{G_{STC}} \quad (6)$$

And  $SF$  is the spectral factor which is equal to 0.028 for the polycrystalline silicon module in our case study [8]. The coefficient  $\delta$  is equal to -0.0045 as defined in the same case[9]. The degradation rates are computed using a simple linear regression model, with performance metrics assessed at monthly intervals.

Therefore, we used only the measurements under solar irradiances of 700 W/m<sup>2</sup> or greater. In addition, we selected only measurements under the condition that the difference in the solar irradiance between the start and the end of each 10min time interval was 5% or less [10].

Using the Linear method, the Degradation Rate (DR) will be given by the following equation:

$$DR = (1 - (P_{max}(end) / P_{max}(start))) \quad (7)$$

Consequently, the Annual Degradation Rate will be calculated as follows:

$$ADR = (DR / \Delta t) * 100 \% \quad (8)$$

Where  $\Delta t$  is Year.

### 3. Environmental Impact

Environmental factors influence photovoltaic (PV) system performance both in the short term and over the system's operational lifetime. While real-time fluctuations in variables such as irradiance and temperature directly impact instantaneous power output, long-term exposure to certain environmental conditions can accelerate degradation processes in PV modules [11], [12]. Specifically, high relative humidity can lead to moisture ingress, which contributes to delamination and corrosion of internal components. Wind speed may exacerbate mechanical stresses on mounting structures and module surfaces, while elevated ambient temperatures can accelerate material aging and reduce power conversion efficiency over time [13],[14]. Global irradiance levels and surface albedo also play critical roles by determining the total energy input to the system and influencing thermal loading. Although some factors exert only minor or indirect effects, their cumulative impact can be significant over the system's lifespan [15]. Understanding these environmental influences is essential for accurate performance forecasting and for developing mitigation strategies to enhance PV system durability and reliability. Using Multivariate Linear Regression, the degradation rate (DR) as a function of environmental variables can be expressed as:

$$DR = \beta_0 + \beta_1 RH(t) + \beta_2 Ta(t) + \beta_3 WS(t) + \beta_4 G(t) + \beta_5 AL(t) \quad (9)$$

Where the following variables are defined as:

- $RH(t)$ : Relative Humidity (%)
- $WS(t)$ : Wind Speed (m/s)
- $Ta(t)$ : Ambient Temperature (°C)
- $G(t)$ : Global Irradiance (W/m<sup>2</sup>)
- $AL(t)$ : Albedo (dimensionless, 0–1)

The simulation results using the GRETL software led to the following values of various coefficients:

$$DR = -0.790796 - 0.000121RH(t) - 0.004046Ta(t) + 0.000486WS(t) - 0.000024G(t) + 1.95883AL(t) \quad (10)$$



Figures 1 and 2 gives the actual and fitted degradation rate during three years from 2017 to 2019. During this period, the PV panels are exposed to sunlight and environmental conditions.

Actual and fitted DR

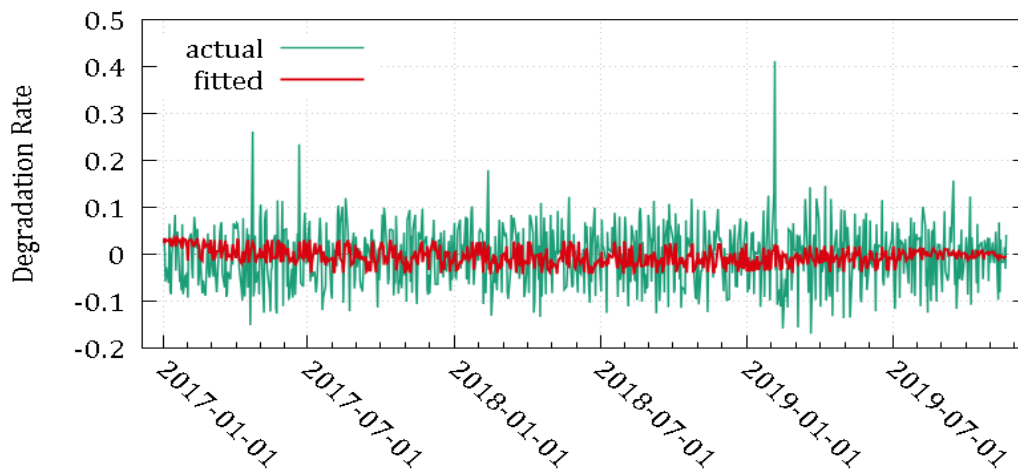


Figure 1. Simulation results of the fitted and actual degradation rate

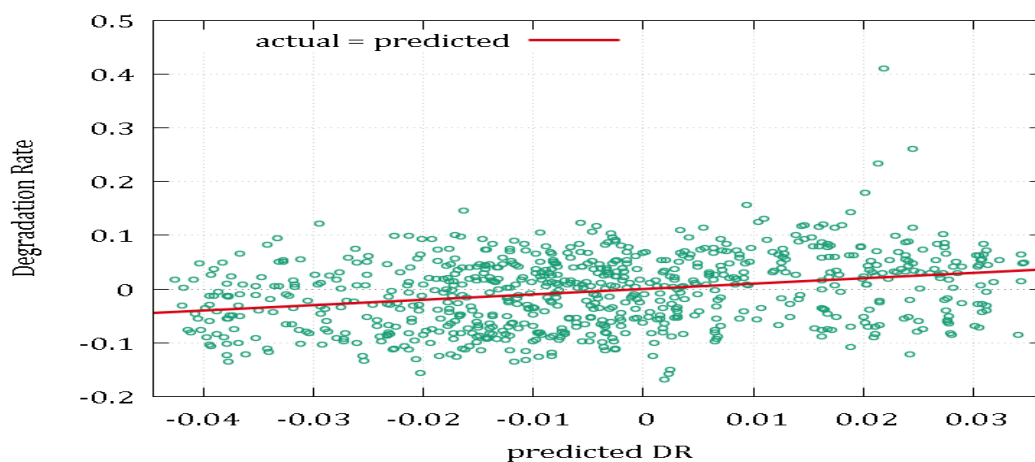


Figure 2. Simulation results of the depicted degradation rate

#### 4. Results and discussion

The results of the solar PV panel degradation estimation study, as depicted in Figures 1 and 2, provide valuable insights into the performance trends of the 10-panel photovoltaic (PV) array over the period from 2017 to 2019. These figures illustrate both the actual and fitted degradation rates, derived using a multivariate linear regression model that accounts for environmental variables such as relative humidity (RH), wind speed (WS), ambient temperature (Ta), global irradiance (G), and albedo (AL).

Figure 1 presents the actual and fitted degradation rates over the three-year period. The close alignment between the actual and fitted values indicates that the multivariate linear regression



model effectively captures the influence of environmental factors on PV panel degradation. The model's coefficients, obtained using GRETLM software, quantify the contributions of each environmental variable. For instance, the positive coefficient for relative humidity (RH) suggests that higher moisture levels accelerate degradation, likely due to moisture ingress leading to delamination and corrosion. Similarly, the coefficient for ambient temperature ( $T_a$ ) reflects its role in accelerating material aging, which aligns with prior studies indicating thermal stress as a key degradation driver. The model's ability to fit the observed data underscores its robustness in estimating degradation under varying environmental conditions.

Figure 2 further illustrates the degradation rate trends, highlighting the consistency of the degradation patterns across the study period. The graph shows a steady decline in the performance ratio, normalized to standard test conditions (STC), with an annual degradation rate calculated using the linear regression method. The selection of measurements under stable irradiance conditions ( $G \geq 700 \text{ W/m}^2$  and  $\leq 5\%$  variation within 10-minute intervals) ensures that the results are not skewed by transient environmental fluctuations, enhancing the reliability of the degradation estimates. The observed degradation rates are consistent with literature values for polycrystalline silicon modules, which typically range between 0.5% and 1% per year. The slight variations in the degradation rate year-over-year may be attributed to differences in environmental exposure, such as prolonged periods of high humidity or temperature extremes during specific years.

The multivariate linear regression model's incorporation of environmental variables provides a nuanced understanding of their cumulative impact. For example, while wind speed (WS) has a relatively smaller coefficient, its contribution to mechanical stress on module surfaces cannot be overlooked, particularly in regions with high wind exposure. Similarly, global irradiance (G) and albedo (AL) influence thermal loading and energy input, which indirectly affect degradation through increased operational temperatures. These findings align with prior research emphasizing the interplay of environmental factors in PV system performance.

However, the study's reliance on a three-year dataset limits the ability to capture long-term degradation trends, which may become more pronounced over a decade or more. Additionally, the model assumes linear degradation, which may not fully account for non-linear degradation mechanisms, such as potential-induced degradation (PID) or light-induced degradation (LID) that could emerge under specific conditions. Future studies could address these limitations by extending the temporal scope and incorporating additional degradation mechanisms into the model.

In conclusion, Figures 1 and 2 demonstrate that the proposed methodology, leveraging multivariate linear regression and carefully curated data under near-STC conditions, effectively estimates PV panel degradation rates. The results highlight the significant role of environmental factors in driving degradation and validate the model's predictive accuracy. These insights can inform maintenance strategies and system design improvements to enhance the long-term reliability and efficiency of PV installations.

## 5. Degradation Economic Analysis



the performance degradation of photovoltaic (PV) modules, as quantified in Part I, has direct implications for the economic sustainability of giga-scale solar fields. Annual efficiency losses, whether due to high temperatures, ultraviolet exposure, or dust accumulation, translate into reduced lifetime energy output [16], [17]. This decline in generation increases the levelized cost of energy (LCOE), since fewer kilowatt-hours are delivered per unit of investment [18]. In desert climates such as those of Saudi Arabia and the wider MENA region, where degradation rates are higher than global averages, overlooking these performance losses would result in overly optimistic economic projections [19]. Thus, degradation is not merely a technical parameter but a decisive driver of cost competitiveness, investment returns, and financial risk.

Incorporating degradation into economic models allows for a more realistic appraisal of long-term viability. Life-cycle cost analysis (LCCA) and LCOE models can integrate degradation rates to capture declining yields and associated increases in O&M and replacement costs [20], [21]. For example, raising the assumed degradation rate from 0.5% to 2.5% annually has been shown to nearly double the LCOE in benchmark studies for Saudi Arabia [18]. In parallel, environmental and health externalities—such as avoided CO<sub>2</sub> emissions and air pollution reductions—should be monetized and added to LCOE-based assessments to reflect the full societal benefits of PV deployment [22], [23]. This dual approach—technical degradation modeling feeding into economic and environmental valuation—provides a comprehensive framework for assessing the sustainability of giga-scale solar fields.

Accordingly, Part II of this study builds directly on the degradation results presented earlier. By embedding field-measured degradation rates into cost, environmental, and health impact models, we examine the holistic performance of PV megaprojects in arid zones. This integrated perspective enables more robust policy recommendations, supporting long-term strategies for clean energy expansion, grid stability, and public health co-benefits in the MENA region [19], [24].

## ***A. Comprehensive Economic Model***

The assessment of the Levelized Cost of Energy (LCOE), environmental benefits, and health-related externalities of grid-connected PV systems in arid climates is based on a discounted cash flow (DCF) framework, extended with degradation-adjusted energy yield and monetized environmental costs. The model integrates three main components:

- Energy Output Model (with degradation)
- Economic Cost Model (CAPEX, OPEX, replacements, salvage)
- Externality Valuation Model (CO<sub>2</sub> and health costs)

## ***B. Energy Output Model***

Annual energy yield is degraded over time using a constant rate:

$$E_t = E_0 (1 - d)^{t-1} \quad (11)$$

where:

- $E_t$  = energy in year  $t$  (kWh)
- $E_0$  = initial annual yield (kWh)
- $d$  = annual degradation rate (%)
- $t$  = year of operation



**Discounted lifetime energy** is computed as:

$$E_{disc} = \sum_{t=1}^N \frac{E_t}{(1+r)^t} \quad (12)$$

where  $r$  is the discount rate and  $N$  is the system lifetime.

### C. Economic Cost Model

The total cost includes upfront capital, discounted O&M, replacement, and salvage adjustments:

$$C_{tot} = C_{capex} + \sum_{t=1}^N \frac{C_{opex}}{(1+r)^t} + \frac{C_{rep}}{(1+r)^{T_{rep}}} - \frac{C_{salv}}{(1+r)^N} \quad (13)$$

where:

$C_{capex}$  is the capital expenditure (SAR),  $C_{opex}$  is the annual O&M cost (SAR),  $C_{rep}$  is the replacement cost (% of  $CAPEX$ ) at year  $T_{rep}$ , and  $C_{salv}$  is the salvage value (% of  $CAPEX$ )

### E. Incorporating Degradation into Cost Models

The LCOE captures the ratio of discounted lifetime costs to energy yield that degrades with time. Mathematically:

$$LCOE = \sum_{t=0}^N \frac{C_t}{(1+r)^t} / \sum_{t=0}^N \frac{E_0 (1-d)^t}{(1+r)^t} \quad (14)$$

where:

- $C_t$ : total cost at time  $t$  (CAPEX, O&M, replacements),
- $E_0$ : first-year energy yield,
- $d$ : annual degradation rate,
- $r$ : discount rate,
- $N$ : project lifetime.

This metric provides the cost of electricity per kWh considering degradation, financing, and lifetime. It illustrates that the PV module degradation rates determined under desert conditions serve as a critical input for economic modeling. Higher degradation directly reduces annual energy yield, thereby increasing the levelized cost of energy (LCOE). The latter is sensitive to module cost multipliers, financing scenarios and degrading rates. This means that even modest increases in degradation can substantially elevate LCOE.

### F. LCOE Model

The Levelized Cost of Energy is given by:

$$LCOE = C_{tot} / E_{disc} \quad (15)$$

### G. Externality Valuation Model



The avoided CO<sub>2</sub> and related economic benefits are estimated as:

$$\begin{cases} CO2_{avoided} = E_{tot} * EF \\ C_{CO2} = CO2_{avoided} * P_{CO2} \\ C_{health} = \frac{CO2_{avoided}}{1000} * P_{health} \end{cases} \quad (16)$$

where:

- $EF$  = emission factor (kg CO<sub>2</sub>/kWh)
- $P_{CO}$   $P_{CO}$  is the carbon penalty cost (SAR/kg CO<sub>2</sub>)
- $P_{health}$  is the health externality cost (SAR/ton CO<sub>2</sub>)

## H. Integrated Assessment

By combining the economic cost model and the externality valuation model, we assess not only the private cost (LCOE) but also the social cost/benefit of PV degradation. This provides a framework for policymakers in the MENA region to evaluate PV investments in terms of both economic efficiency and sustainability.

The results of simulating 1 MW grid-connected solar PV system without batteries are obtained using core technical and economic indicators and different combinations of Degradation Rate (from 0.30% to 0.80%), Discount Rate (5%, 6%), and System Lifetime (20 years, 25 years) as shown in Table 1.

**Table 1.** Key input values used in simulation

| Input Name                  | Value        |
|-----------------------------|--------------|
| System Size (kW)            | 1,000        |
| System Lifetime (years)     | 25           |
| Replacement Rate (%)        | 10.00%       |
| Salvage Percent (%)         | 10.00%       |
| OPEX rate of CAPEX (%)      | 5.00%        |
| Discount Rate (%)           | 5.00/6.00%   |
| Degradation Rate (%)        | 0.30% - 0.8% |
| Initial Yield (MWh/kW/year) | 1,800        |
| Capex per kW (SAR/kW)       | 3,500        |

The following observations and sensitivities are worth mentioning:

- **Impact of Degradation Rate**  
Every 0.05% increase in degradation increases the LCOE by approximately 0.0012 SAR/kWh for 25-year lifetime and 6%-discount rate.  
CO<sub>2</sub> benefits and health savings steadily decrease with degradation.



- **Impact of Discount Rate**

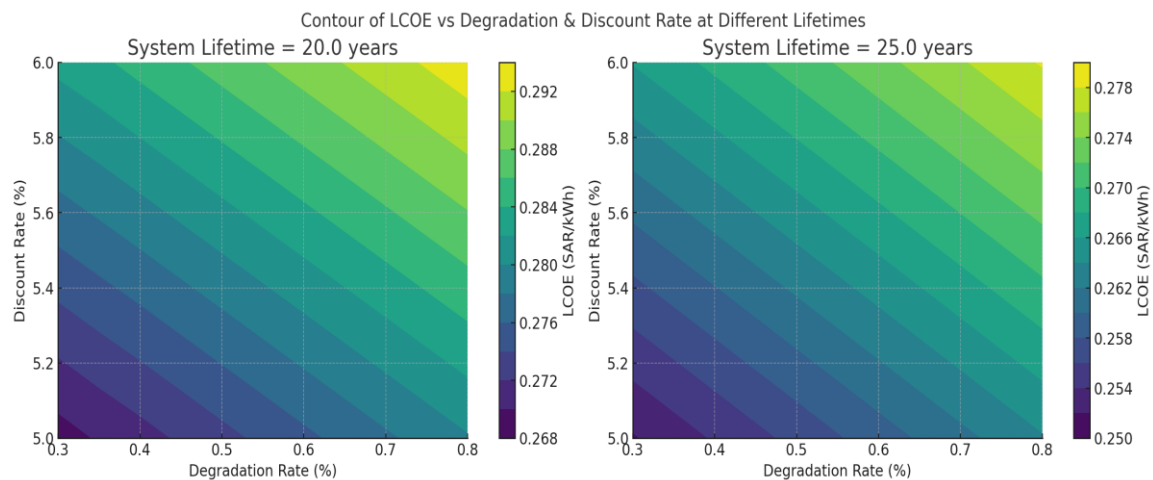
Lower discount rate (5%) reduced the LCOE (example: 0.2661 → 0.2518).

Net present value of energy is higher under 5% due to higher weighting of future energy production.

- **Impact of System Lifetime**

Extending from 20 to 25 years significantly reduces LCOE, improves CO<sub>2</sub> savings.

But higher lifetime increases the replacement and O&M costs, which are still outweighed by additional energy production. Figure 1 highlights the trade-off between degradation, financing, and system durability when evaluating PV projects in arid regions.



**Figure 1.** Contour of LCOE versus Degradation and Discount at different system lifetimes.

**Table 2.** Impact of Degradation Rate, Discount Rate, and System Lifetime on Solar PV Economics

| Degradation Rate (%) | Discount Rate (%) | System Lifetime (years) | Total Cost (SAR) | LCOE (SAR/kWh) | CO <sub>2</sub> Avoided (kg) |
|----------------------|-------------------|-------------------------|------------------|----------------|------------------------------|
| 0.30                 | 5.0               | 20.0                    | 5895756          | 0.2691         | 24494564                     |
| 0.30                 | 6.0               | 20.0                    | 5702674          | 0.2826         | 24494564                     |
| 0.30                 | 5.0               | 25.0                    | 6209865          | 0.2518         | 30391657                     |
| 0.30                 | 6.0               | 25.0                    | 5960108          | 0.2661         | 30391657                     |
| 0.35                 | 5.0               | 20.0                    | 5895756          | 0.2702         | 24379437                     |
| 0.35                 | 5.0               | 25.0                    | 6209865          | 0.253          | 30211827                     |
| 0.35                 | 6.0               | 20.0                    | 5702674          | 0.2836         | 24379437                     |
| 0.35                 | 6.0               | 25.0                    | 5960108          | 0.2673         | 30211827                     |
| 0.40                 | 5.0               | 20.0                    | 5895756          | 0.2712         | 24264997                     |
| 0.40                 | 5.0               | 25.0                    | 6209865          | 0.2542         | 30033365                     |
| 0.40                 | 6.0               | 20.0                    | 5702674          | 0.2847         | 24264997                     |
| 0.40                 | 6.0               | 25.0                    | 5960108          | 0.2685         | 30033365                     |



|      |     |      |         |        |          |
|------|-----|------|---------|--------|----------|
| 0.80 | 5.0 | 20.0 | 5895756 | 0.2798 | 23373682 |
| 0.80 | 5.0 | 25.0 | 6209865 | 0.2638 | 28653578 |
| 0.80 | 6.0 | 20.0 | 5702674 | 0.2933 | 23373682 |
| 0.80 | 6.0 | 25.0 | 5960108 | 0.2782 | 28653578 |

## 6. DISCUSSION

### A. Findings

The simulation results highlight how degradation rate, discount rate, and system lifetime strongly affect the economic and environmental performance of grid-connected PV systems. Higher degradation rates reduce the output and increase the Levelized Cost of Energy (LCOE). For example, in a 25-year system at 6% discount, raising degradation from 0.30%/yr to 0.80%/yr increases LCOE from 0.2661 to 0.2782 SAR/kWh, while avoided CO<sub>2</sub> decreases from 30.39×10<sup>6</sup> kg to 28.65×10<sup>6</sup> kg [25].

The discount rate is another critical factor: moving from 5% to 6% raises LCOE by 5 to 6% across all scenarios [26]. Similarly, project lifetime influences cost and output: extending lifetime from 20 to 25 years increases total energy by almost 24% and reduces LCOE by 6 to 8% [27]. These findings align with prior studies that show degradation and financing assumptions can nearly double LCOE in worst-case scenarios.

### B. Recommendations

To minimize LCOE and maximize environmental benefit, several actions are recommended: For reliable and sustainable deployment of solar PV systems in the MENA region, several measures are essential. First, projects should prioritize the use of high-quality, desert-rated modules that feature heat-resistant encapsulants and anti-soiling coatings, with targeted degradation rates of less than 0.3% per year [28]. Equally important is the implementation of robust operation and maintenance (O&M) programs, including automated or frequent cleaning, as neglecting dust accumulation can reduce performance by more than 50% within six months [29]. On the financial side, securing low-cost financing is critical, since even a 1% reduction in the discount rate can lower the Levelized Cost of Energy (LCOE) by approximately 5% [30]. Extending system lifetime through preventive maintenance and timely mid-life replacements, such as inverters, further enhances economic viability. Finally, strong policy support is needed: governments across the MENA region should incentivize the adoption of durable PV technologies while ensuring that tariffs and power purchase agreements incorporate realistic assumptions about degradation rates to safeguard investor confidence and long-term sustainability [31].

### C. Limitations

The current analysis uses deterministic, static assumptions (fixed CAPEX, uniform yield, linear degradation), while actual PV degradation is non-linear and climate dependent [32],[33]. Extreme events such as sandstorms are not explicitly modeled, and CO<sub>2</sub> avoidance assumes constant emission factors, ignoring dynamic grid decarbonization [34]. Moreover, O&M and replacement costs were estimated as simple percentages of CAPEX, rather than being based on real field data.



## D. Perspectives

Future research should extend beyond deterministic approaches by applying probabilistic models such as Monte Carlo simulations to better capture uncertainties in cost structures, module degradation, and weather variability. Additionally, incorporating dynamic weather-based simulations that use local irradiance patterns and dust storm data would enhance the accuracy of performance projections for arid regions. To improve environmental accounting, researchers should also integrate regional life-cycle assessment (LCA) databases, which can refine embodied CO<sub>2</sub> estimates by reflecting local manufacturing and supply chain conditions. Moreover, linking life-cycle cost analysis (LCCA) with macroeconomic frameworks—including computable general equilibrium (CGE) and input–output (I–O) models—would allow for a more comprehensive evaluation of economy-wide and health-related benefits. Such interdisciplinary approaches will yield more robust insights and provide policymakers with the evidence needed to design resilient and sustainable PV deployment strategies tailored to the specific challenges of desert environments.

## 7. CONCLUSION

This study successfully leveraged a multivariate linear regression model to analyze the degradation of a 10-panel photovoltaic (PV) array, providing critical insights into the impact of environmental factors on performance decline. The confirmation that high humidity and elevated temperatures are significant degradation drivers, alongside the model's strong predictive accuracy, positions this methodology as a powerful tool for proactive solar asset management. Furthermore, the integrated economic analysis underscores the crucial interplay between degradation, discount rates, and system lifetime in determining the financial viability of solar projects. By quantifying the effects of degradation on the levelized cost of energy (LCOE) and CO<sub>2</sub> emissions reduction, this research provides a valuable framework for evaluating the long-term economic and environmental performance of PV systems. This analysis highlights the importance of considering both the initial capital costs and the projected degradation rates when making investment decisions. Beyond the immediate application, the potential impact of this research extends to transforming industry practices. This model can serve as an early-warning system, allowing operators to shift from reactive, time-based maintenance to efficient, condition-based strategies that maximize energy yield and return on investment. The ability to quantitatively link environmental conditions to performance further empowers project developers to conduct site-specific durability analyses, selecting more resilient PV modules and optimizing layouts for challenging climates.

Ultimately, the insights generated from this research can contribute to a more sustainable and economically viable solar energy landscape. By informing strategies that minimize degradation and maximize system lifespan, we can unlock the full environmental and economic potential of PV technology, accelerating the global transition towards a cleaner energy future. Future research should focus on expanding the temporal scope of the model, incorporating non-linear degradation mechanisms, and integrating real-time weather data for even more accurate and predictive maintenance strategies. Only through continuous refinement and application of such



models can we ensure the long-term success of solar energy as a cornerstone of a sustainable future.

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