Long-Term Effects of Degradation on Photovoltaic System Return on Investment

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***Abstract*—The adoption of photovoltaic (PV) systems has increased significantly in recent years, driven by the demand for off-grid and on-grid residential and commercial applications. However, the high initial investment required for PV installations has limited their widespread adoption. Governments and marketing enterprises have implemented different strategies to promote PV systems to overcome this barrier, focusing on the return on investment (ROI) concept. However, the conventional approach uses limited economic factors to calculate the ROI. It fails to consider the impact of external factors, such as system degradation, which can vary between systems. To address this issue, we propose a new methodology to estimate the ROI of a photovoltaic system with greater accuracy. Our approach incorporates system-predicted degradation, calculated using historical meteorological data and prediction techniques. We applied this methodology to a photovoltaic system installed at the Universidad Tecnológica de Bolívar (UTB) in Cartagena and evaluated it against five different approaches. The results show that our proposed method offers a more accurate and reliable estimation of the ROI of a photovoltaic system, considering a broader range of factors. Overall, our work contributes to advancing the understanding of photovoltaic system ROI calculation and promotes using sustainable energy sources. By providing a more precise estimation of the ROI of a photovoltaic system, our methodology can help potential investors make more informed decisions and promote the adoption of clean energy sources.**

***Index Terms*—Photovoltaic System, Performance Indicator, Degradation Model, Return on Investment.**

I. Introduction

The adoption of photovoltaic (PV) systems in Latin America has increased significantly in recent years [1], as individuals and businesses seek to utilize clean energy sources [2]. However, the high cost of installing PV systems has deterred many potential investors, [3] despite government efforts to implement renewable fit schemes that reduce the spot price of PV components [4].

Market enterprises tend to focus on promoting PV systems using a fast ROI strategy to attract more investors. However, calculating the ROI of a PV system is a complex process that involves considering multiple factors, [5], such as taxes, inflation [6], opportunity cost, regional rewards [7], energy efficiency, and component degradation [8].

The conventional ROI calculation method assumpts an ideal PV system that generates electricity, the customer consumes all power [9], and the annual electric output, taxes, and incentive policies remain constant [10]. Yet, this method needs to account for the impact of external factors that can affect the performance of PV systems, making it difficult to assess the actual ROI accurately.

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Several studies have attempted to address this issue by proposing new approaches to calculating the ROI of PV systems [11]. However, these approaches often require considerable time and resources, making them impractical for many potential investors [12].

This study proposes a novel approach to address these challenges for designing and calculating the ROI of a photovoltaic system situated at the Universidad Tecnológica de Bolívar (UTB) in Cartagena, Colombia. Fig. 1 visually represents the proposed installation site for the photovoltaic solar plant at UTB. The figure is divided into four sections to offer a comprehensive view of the location, encompassing key features such as the UTB campus, specific areas designated for solar plant installation, and the current location of the UTB meteorological station, which holds significant relevance to our research.

The proposed methodology involves a six-step approach that first considers historical data from UTB and historical production data of a system installed near the UTB and with similar PV capacity. Then, we processed the historical by the long short-term memory (LSTM) model [13] to predict the production of the designed system. Then, we used the results to calculate the performance indicator (PI), the degradation curve, and the return on investment.

Estimating the ROI of photovoltaic (PV) systems is crucial for promoting the adoption of sustainable energy sources. We compared our proposed approach for calculating PV system ROI with five other approaches by analyzing the actual ROI curve. The results showed that the zero degradation, low degradation, and middle degradation approaches estimated the ROI at five years, while our approach estimated the ROI at year eight. Our approach took into account the performance indicator PI of the PV system, which enabled us to calculate a more accurate ROI than other approaches.

Furthermore, our study reveals that the ROI takes longer when the PV system has programmed clean sessions. This finding suggests that future work could estimate the best times to schedule maintenance sessions to avoid overcleaning the system.

The accuracy of our proposed approach has significant implications for sellers and policymakers. Sellers can provide a more precise ROI estimate, leading to better economic satisfaction for clients in the short and long term. Policymakers can implement effective renewable energy policies based on accurate ROI calculations, promoting the use of sustainable energy sources in Latin America and contributing to a more sustainable future.

Overall, our proposed approach for estimating PV system

Fig. 1. Proposed Photovoltaic Solar Plant Installation Site at UTB and Current Location of UTB Meteorological Station

ROI provides a more accurate estimation of the ROI, which is essential for promoting the use of sustainable energy sources in Latin America that contribute to advance in the understanding of PV system ROI calculation and can inform the development of practical renewable energy policies.

II. Related Work

Previous research has explored various aspects of estimating photovoltaic systems' performance and economic viability. This section provides a concise overview of key studies and highlights their contributions to our research. We emphasize how our work extends and differentiates itself from prior approaches.Our research stands out by evaluating and comparing various state-of-the-art approaches while introducing a novel methodology that considers critical factors often overlooked in ROI calculations. We explicitly account for system degradation and maintenance costs, providing decision-makers with a more accurate assessment of a photovoltaic system's financial performance over time.

A. Economic Factors and ROI

Muhammad et al. [14] introduced an approach that considers economic factors to evaluate future cash flows in photovoltaic systems. While they addressed financial considerations, our study takes a step further by introducing a novel methodology that explicitly incorporates critical factors often overlooked in ROI calculations, such as system degradation and maintenance costs.

B. Energy Return on Investment (EROI)

Zhou et al. [15] introduced the Energy Return on Investment (EROI) concept to measure the electrical energy output versus electrical energy inputs in photovoltaic systems. Our work concentrates on ROI assessment but provides a unique contribution by integrating degradation modeling and maintenance cost analysis, providing a more holistic financial perspective.

C. Financial Performance and Simulation

Ozcan et al. [16] focused on ROI based on financial performance, utilizing a photovoltaic simulator for production estimation. In contrast, our research distinguishes itself by introducing a comprehensive approach that explicitly considers the impact of degradation and maintenance on ROI, leading to more accurate financial projections.

D. Internal Rate of Return (IRR) and Net Present Value (NPV)

Ertuugrul et al. [17] used financial metrics like Internal Rate of Return (IRR) and Net Present Value (NPV) to assess ROI. Our study complements these metrics by incorporating a degradation model, providing insights into long-term performance trends and their financial implications.

E. Maintenance and Component Replacement

When calculating ROI, Formica et al. [18] factored in annual taxes, component failures, maintenance costs, and component replacements. Our research builds upon these considerations by introducing a comprehensive degradation model that captures the long-term performance decline of photovoltaic systems.

F. Long-Term Efficiency and Degradation Analysis

Seo et al. [19] analyzed photovoltaic production efficiency and degradation percentages based on seven years of data. Our work follows a similar trajectory by considering long-term data but distinguishes itself by incorporating a degradation model that quantifies the impact of performance decline on ROI.

G. Reliability and Durability Assessment

Using monthly production data, Dhimish et al. [20] presents a straightforward method for estimating degradation rates in photovoltaic panels by accurately quantifying power output decline over time. This approach enhances monitoring precision and facilitates comparisons with existing degradation estimation technologies.

III. Methodology

This section outlines our comprehensive methodology for assessing the Return on Investment ROI of the proposed 60.8 kW (DC) photovoltaic solar system intended for installation at the Universidad Tecnológica de Bolívar UTB in Cartagena, Colombia. Our approach encompasses several key components, each contributing to a comprehensive ROI evaluation.

TABLE I
PRESENCE OF VARIABLES IN DATASETS

Variable	Unit	Dataset 1	Dataset 2	Dataset 3	Dataset 4
Date	d.m.Y h	✓	✓	✓	✓
Irradiation	W/m²	✓	✓	✓	✓
Ambient Temperature	°C	✓	✓	✓	✓
Module Temperature	°C	✓	✓	-	✓
Apparent Power (S)	VA	✓	✓	-	✓
Reactive Power (Q)	VAr	✓	✓	-	✓
PV Production	Wh	✓	✓	-	✓
Humidity	g/m³	-	-	✓	-
Pressure	Pa	-	-	✓	-

A. Historical Data

Table I summarizes essential variables found in three historical datasets used for our analysis. Included variables encompass date, irradiation, ambient temperature, module temperature, apparent power (S), reactive power (Q), PV production, humidity, and pressure. Checkmarks indicate whether each dataset contains these variables.

1) Dataset 1: Maintained Photovoltaic System: We derived Dataset 1 from a meticulously maintained photovoltaic system approximately 5 kilometers from UTB. This system undergoes regular monitoring and follows a comprehensive cleaning protocol. Every four months, a thorough cleaning process is executed during daylight hours, utilizing demineralized water and an advanced cleaning robot. The dataset encompasses detailed records retrieved from the Fronius Web Platform, which meticulously tracks the operation of a three-phase inverter (AC) integrated into a high-capacity 60.8 kW (DC) photovoltaic solar system. Additionally, it includes invaluable meteorological data that holds significant relevance for our comprehensive analysis. Historical data for this system spans over three years, providing a rich and robust foundation for our research.

2) Dataset 2: Non Maintained Photovoltaic System: In contrast, Dataset 2 comes from a non-maintained 180 kW (DC) photovoltaic system situated approximately 8.7 kilometers from UTB. This dataset includes data recorded by a three-phase inverter (AC) but lacks the structured maintenance observed in Dataset 1.It also incorporates essential meteorological data. The historical data for this system also spans over two years.

3) Dataset 3: Meteorological Data from UTB's Location: Dataset 3 comprises a comprehensive set of meteorological data collected over a robust five-year period. We collected these records from a weather station atop UTB in Cartagena, Colombia. The dataset encompasses key parameters, including solar irradiance, ambient temperature, humidity, and atmospheric pressure.We applied rigorous preprocessing procedures to eliminate anomalies, including null values and erratic variable behavior, such as negative irradiance readings or nighttime data points. Notably, the weather station will be no more than 60 meters from where the UTB photovoltaic plant will be.

4) Dataset 4: UTB Synthetic Historical Data: In addition to the three primary datasets mentioned earlier, we employed a supplementary dataset comprising synthetic historical data. We generated these synthetic data using the System Advisor Model (SAM) online simulator, a renowned software tool developed by the National Renewable Energy Laboratory (NREL) [21]. SAM offers robust simulation features, allowing us to generate reference production profiles based on the UTB system's design specifications and geographical coordinates of the UTB location (latitude: 10.370372147751306, longitude: -75.46543750536256). The synthetic historical data serve as an invaluable resource for our analysis, providing a controlled and idealized reference for the expected energy production of the UTB photovoltaic system under various conditions. These synthetic data further enhance the comprehensiveness of our ROI estimation methodology, allowing us to evaluate the performance and financial viability of the UTB photovoltaic system with a high degree of accuracy and confidence. To construct our methodology, we utilized three primary datasets to ensure robustness and relevance. We meticulously chosen each dataset based on location proximity and historical data availability

B. Production Predictor Model Implementation

In this research phase, we rigorously applied our production prediction model, following the methodology proposed by Martinez et al. (2022) for accurately predicting solar photovoltaic (PV) energy production and associated climatic conditions. Our primary objective, within the context of this model, is to achieve precise and reliable forecasts of energy production for the planned 60.8 kW (DC) PV system intended for deployment at the UTB.

Our adaptation of Martinez et al.'s methodology consists of two phases.

1) Phase One: Training and Validation: The initial phase involved a systematic division of Dataset 1 and Dataset 2 into separate subsets designated for training and validation, maintaining an 80-20 split ratio. Then, we applied the LSTM (Long Short-Term Memory) neural network, a robust tool for sequence prediction tasks. This phase incorporated historical production records, irradiance levels, and temperature data. Remarkably, our inference model achieved an impressive level

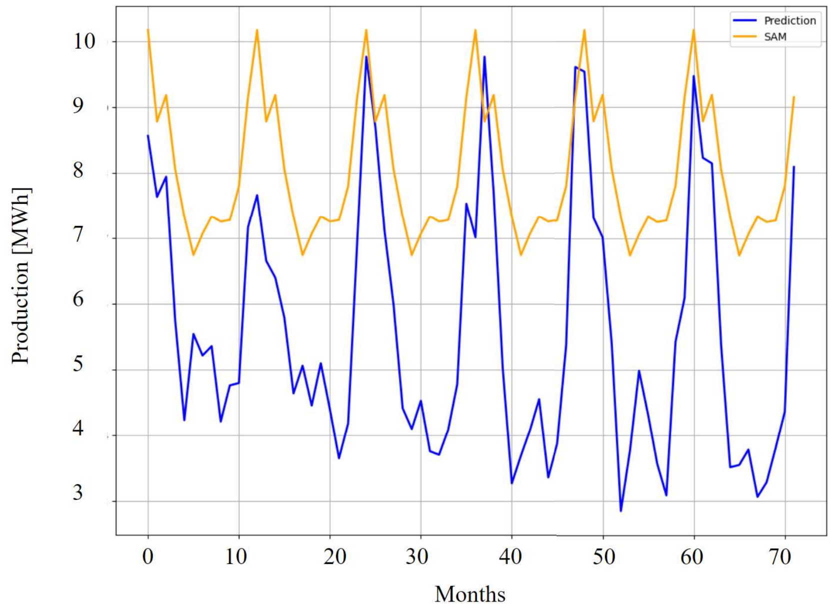

Fig. 2. This figure depicts the projected production of the UTB PV system over 72 months using Martinez et al.'s methodology. It also compares this projection with the idealized production estimate from the SAM simulator, enabling an assessment of real-world system performance against an idealized projection.

of accuracy, with a remarkable 94% on the training dataset and a robust 90% on the validation dataset.

2) Phase Two: Predictive Analysis: In the second phase of our research, we faced the challenge of predicting the energy production expected from the upcoming UTB PV system, armed with our meticulously trained inference model. To achieve this, we seamlessly integrated historical irradiance and temperature data from Dataset 3 into our model. To enhance the accuracy of our predictions, we conducted a comparative analysis between our production projections and the idealized outcomes generated by the synthetic Dataset 4, as illustrated in Fig. 2. While both projections display similar patterns, the key distinction lies in Dataset 4's model, which leans towards an idealized scenario. In contrast, our model embraces a grounded approach, aligning more closely with the nuanced fluctuations in temperature and irradiance observed over a comprehensive 72-month timeframe. This critical differentiation underscores the real-world applicability of our model, as it faithfully reflects the historical climatic factors of the region, resulting in a more conservative production estimate that aligns with practical operational outcomes.

C. Evaluation of Performance Indicator

The Performance Indicator PI is a crucial metric that quantifies how effectively the photovoltaic system performs compared to its idealized simulation [22]. It establishes a relationship between the monthly production data, recorded hourly from the photovoltaic system, and the monthly expected production.

This essential relationship is in Equation 1:

$$PI = \frac{\sum \text{Monthly System Production}}{\sum \text{Monthly Expected Production}} \quad (1)$$

The PI provides valuable insights into the real-world efficiency of the photovoltaic system. A PI value above 100 indicates that the system outperforms its simulated expectations, reflecting a favorable operational outcome. Conversely, a PI below 100 suggests underperformance.

To calculate the PI, we utilize real-world production data extracted from historical records (specifically, synthetic Dataset 4) and the production projections generated by our production prediction model, as explained in the previous section. This combination of actual and simulated data allows us to gauge the practical performance of the photovoltaic system against its simulated ideal.

D. Degradation Curve

We used our knowledge of previously calculated Performance Indicator PI values in the previous phase of our degradation forecasting process. Our primary goal in this phase was to establish a precise mathematical representation, clarifying the temporal behavior of the Performance Indicator PI. To achieve this, we employed an exponential decay function. While in the preceding phase, we were able to determine discrete PI values using production predictions and synthetic Dataset 4, these were merely isolated data points. However, we intended to capture a more continuous trend in the data. Hence, we proposed an exponential decay curve shown in equation 2, which, in this context, symbolizes the system's underperformance or what we refer to as the degradation curve.

$$y(x) = a \cdot e^{-b \cdot x} \quad (2)$$

In this equation, "x" represents time, while "y" corresponds to the Performance Indicator at specific temporal points. Each data pair "(x, y)" corresponds to a distinct time point and the observed performance.

Following the formulation, we meticulously fine-tuned the parameters "a" and "b" to ensure a precise fit of the exponential

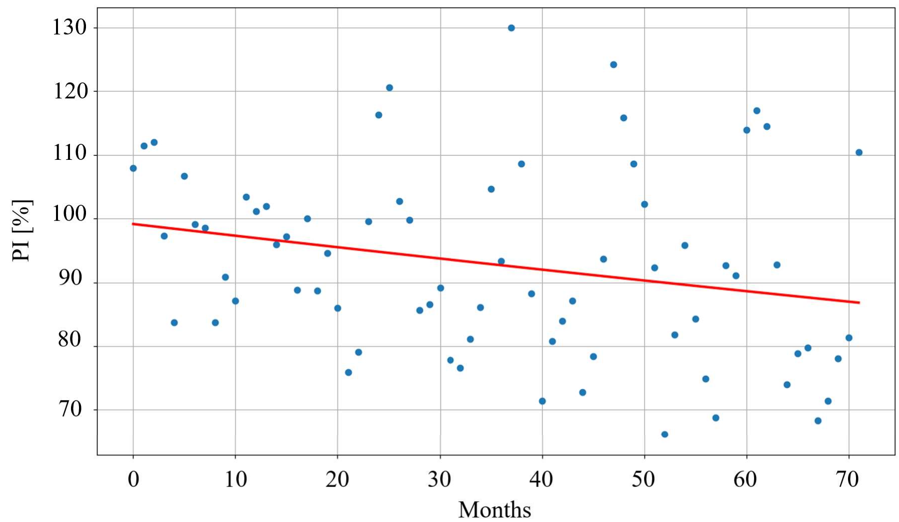

Fig. 3. Degradation fitted curve using the exponential non-linear regression $D(t) = 99.9e^{-0.001227}t$

model to the empirical historical data. We conducted this fine-tuning process using Python curve fitting techniques, ultimately yielding the exponential decay degradation curve:

$$D(t) = a \cdot e^{-b \cdot t} \tag{3}$$

Within equation 3, the parameter "a" signifies the initial Performance Indicator value, while "b" represents the coefficient governing the rate of performance decay over time.

This degradation modeling approach empowers us to predict the long-term performance decline of the photovoltaic system, accounting for both scheduled maintenance and the passage of time. This predictive model is valuable for estimating the system's future performance and optimizing maintenance strategies.

$$D(i) = \frac{1}{12} \sum_{t=12i}^{12(1+i)-1} D(t) \tag{4}$$

Equation 4 is a fundamental component of our ROI estimation methodology, enabling us to calculate the annual returns for the photovoltaic system over the specified period, in this case, months.

The results of the degradation implementation are visualized in Fig. 3, which exhibits the results of the exponential regression obtained through the curve fitting evaluation system spanning 72 months. The decay behavior of the Performance Indicator PI over time is clearly evident in the figure. This observation confirms that the system's performance varies over time, highlighting its significance in determining investment returns.

E. Return on Investment (ROI) Calculation

In our investigation, a significant gap becomes evident between the optimistic assurances that various companies offer, confidently promising investors a rapid Return on Investment (ROI) within just four years and the harsh reality experienced in practical scenarios. Consider, for instance, the photovoltaic systems in Dataset 1 and Dataset 2. Initially, these systems would achieve a four-year ROI. However, a different narrative unfolds as time progresses: after three and two years, respectively, they have reached only two-thirds and a mere half of the promised ROI duration. Surprisingly, neither has managed to recover even half of its initial investment.

Our hypothesis revolves around a critical factor often overlooked or underestimated in these optimistic forecasts—degradation losses. In light of this, our subsequent ROI analysis fully considers the substantial impact of degradation. This approach provides us with a more comprehensive and practical perspective, unveiling the actual financial performance of these photovoltaic systems in real-world conditions.

Therefore, in this section, we embark on a detailed exploration of the mathematical aspects underlying the calculation of ROI, computed using equation 5:

$$ROI(i) = \frac{GFI(i) - COI}{COI} \tag{5}$$

Here, the variable i represents the analysis period in years.

It is crucial to clarify that the variables employed in the ROI calculation are intrinsically connected to the degradation model. Specifically, GFI denotes the Gain From Investment, while COI stands for the Cost Of Investment, assumed to be $70,000 USD in this study.

To compute GFI, we sum the annual production, multiplied by the annual kilowatt-hour (kWh) tariff kWh_{price}, for each year within the analysis period, minus the cost of maintenance (COM). The cost of maintenance, "COM," is defined as $COM = COI \times PM$, where "PM" represents the percentage associated with annual maintenance costs. In the context of this study conducted in Colombia in 2023, kWh_{price} equals 0.26 USD (that increases every year by 7.5% respecting the previous year), and PM represents 2% of the initial installation cost. The full equation for $GFI(i)$ is given by:

$$GFI(i) = \sum_{1}^{i} PV_{annual}(i) \times kWh_{price}(i) - COM \tag{6}$$

TABLE II
COMPARATIVE ANALYSIS OF ROI APPROACHES

Approach	% of degradation	4 Years Δ ROI	Calculated ROI
Zero degradation [15]	0	3.45	39
Low degradation [19]	0.05	3.50	29
Middle degradation [18]	0. 2	3.65	26
Degradation estimate with maintenance	Calculated	6.7	-41
Degradation estimate without maintenance	Calculated	6.9	-39

Within this equation, PV_{annual} represents the annual system production, calculated as:

$$PV_{annual} = PV_{designed} \times t_{sun} \times D(i) \tag{7}$$

In this equation, $PV_{designed}$ represents the planned production capacity (60.8 kW in this case), t_{sun} is equivalent to 365 days $\times 8$ hours per day, and $D(i)$ is the degradation factor for year i. This comprehensive approach allows for a holistic assessment of the photovoltaic system's financial performance, considering annual production, performance, and associated costs.

Integrating degradation data into the ROI model enhances the accuracy of investment return estimations.

IV. Evaluation Methodology

Following our hypothesis, this section comprehensively evaluates the proposed ROI method by comparing it with three state-of-the-art approaches commonly employed for PV system ROI calculations. It introduces two additional methodologies proposed in this article. These comparative assessments, detailed in Table II, aim to objectively assess the efficacy and precision of our methodology in accounting for dynamic system degradation. The approaches, categorized based on their consideration of degradation, are presented with their percentage of degradation, 4-year Δ ROI, and calculated ROI values, allowing for clear and informative comparisons. Additionally, we indicated the data sources for each approach in the table.

A. Zero Degradation:

The zero approach serves as a baseline for evaluating ROI methodologies. It assumes a scenario without scheduled maintenance costs but considers the economic impact of the kWh price.

$$D_{a1}(i) = 100 \tag{8}$$

B. Low Degradation:

The low approach considers a system that experiences a minimal 0.05% degradation rate over time and assumes no maintenance costs, that is $COM = 0$. Additionally, it considers the economic impact of the annual increase in the kWh price.

$$D_{a2}(i) = \begin{cases} 100 & \text{if} \quad i = 1 \\ D_{a2}(i-1) \times 0.0005 & \text{if} \quad i > 1 \end{cases} \tag{9}$$

C. Middle Degradation:

The "Middle" approach accounts for the economic effects of the kWh price and assumes a system with a moderate 2% degradation rate and no maintenance costs that is $COM = 0$.

$$D_{a3}(i) = \begin{cases} 100 & \text{if} \quad i = 1 \\ D_{a3}(i-1) \times 0.02 & \text{if} \quad i > 1 \end{cases} \tag{10}$$

D. Degradation Estimate with Maintenance:

In our "Estimated Maintenance" approach, we assume that the system undergoes maintenance with an associated cost.

$$D_{a4}(i) = D(i) \tag{11}$$

$$COM = COI \times 0.02 \tag{12}$$

In this approach, we consider the Cost of Maintenance (COM), where we set the Maintenance Percentage (PM) at 2% based on common practices in the Colombian market, where the scheduled cleanings and maintenance amount is the 2% of the total installed capacity at the current year's value. In other words, each year, the cost of reassembling the entire system is estimated, and 2% of that cost is a maintenance fee for photovoltaic plants.

E. Degradation Estimate without Maintenance:

Our "Estimated No Maintenance" approach assumes that the system operates without scheduled maintenance, that is $COM = 0$. We calculated the degradation regression curve $\hat{D}(i)$ using data from a dataset representing systems without maintenance.

$$D_{a5}(i) = \hat{D}(i) \tag{13}$$

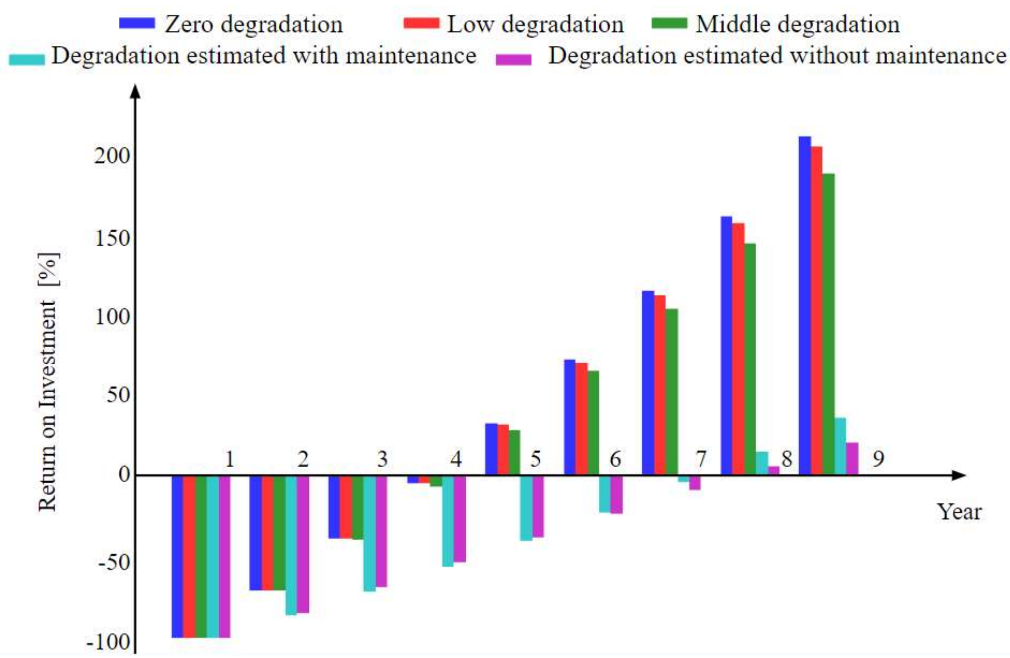

Fig. 4. Evaluated ROI approaches of investment of all five approaches and its calculated difference with the ideal ROI over nine years.

V. Analysis of Results

Table II concisely summarizes the evaluated ROI approaches, offering essential insights into the differences between each methodology's predictions and the actual ROI curve. It is worth noting that all procedures exhibit variations from the actual ROI curve, highlighting the paramount importance of accurately accounting for degradation and maintenance effects.

To better visualize these variations, we have included Fig. 4, which graphically represents the years required to achieve a positive return on investment for each approach. Notably, traditional approaches such as "Zero Degradation," "Low Degradation," and "Middle Degradation" begin to show positive returns starting from the fourth year. In contrast, our proposed methodologies, "Degradation Estimate with Maintenance" and "Degradation Estimate without Maintenance," indicate significantly extended return periods, as depicted in the figure. This observation aligns with the principles of accounting for degradation and maintenance costs, which, although extending the ROI period, provide a more realistic representation of financial returns.

The comparison reveals that traditional methods like "Zero Degradation" and "Low Degradation" yield lower ROI predictions, with "Zero Degradation" resulting in a calculated ROI of 3.45. In contrast, "Low Degradation" shows a calculated ROI of 3.50. These methods assume constant system performance and overlook the economic implications of kWh pricing fluctuations over time.

In contrast, our proposed methodologies, "Degradation Estimate with Maintenance" and "Degradation Estimate without Maintenance," offer a more nuanced perspective on ROI. "Degradation Estimate with Maintenance" accounts for system degradation and maintenance costs, resulting in a calculated ROI 6.7. Conversely, "Degradation Estimate without Maintenance" predicts ROI without considering maintenance costs, yielding a calculated ROI 6.9. These methodologies emphasize the importance of incorporating real-world dynamics into ROI assessments, leading to more accurate estimations.

Our results underscore the critical roles of degradation modeling and maintenance cost considerations in ROI assessments. The proposed methodologies provide an enhanced understanding of ROI by considering these factors and addressing a common discrepancy observed in the field. Decision-makers can use these insights to make well-informed decisions regarding photovoltaic system investments, considering the long-term implications of degradation and maintenance.

VI. Conclusion

In this study, we have addressed a significant challenge in the photovoltaic (PV) industry—the accurate calculation of Return on Investment ROI for PV systems. ROI is a pivotal metric for decision-makers, but its accuracy hinges on the comprehensive consideration of various factors, particularly degradation and maintenance costs. Our research has shed light on these critical aspects and contributed novel methodologies to enhance the precision of ROI estimations.

Through meticulously evaluating five distinct ROI approaches, we have illuminated the disparities between traditional methodologies and those incorporating dynamic system behavior. Our findings emphasize the importance of accounting for PV system degradation and maintenance costs when assessing ROI. Traditional approaches, such as "Zero Degradation" and "Low Degradation," often underestimate ROI by neglecting these factors, ultimately leading to suboptimal investment decisions.

In contrast, our proposed methodologies, "Degradation Estimate with Maintenance" and "Degradation Estimate without Maintenance," provide a more realistic depiction of ROI by integrating degradation modeling and maintenance cost considerations. These methodologies align ROI predictions more closely with system performance and financial implications. Decision-makers can use these approaches to make informed choices, recognizing the long-term impact of degradation and maintenance on their PV system investments.

Furthermore, our research underscores the dynamic nature of PV systems and the necessity of adaptable ROI calculations. Continuous advancements and evolving conditions mark the PV industry, making stakeholders need to employ ROI methodologies that capture these changes accurately.

Finally, this study advances the PV system ROI assessment field by introducing methodologies that consider degradation and maintenance costs. We have demonstrated that such considerations are crucial for achieving ROI predictions that reflect real-world conditions. Our contributions empower decision-makers to optimize their PV system investments, aligning financial expectations with actual performance. As the PV industry evolves, our research is a valuable resource for navigating the complexities of ROI calculations and fostering sustainable solar energy investments.

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