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Integrating solar photovoltaic energy degradation and financial performance for debt service capacity assessment: A life-cycle response surface approach

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ABSTRACT

The development of utility-scale solar photovoltaic projects is subject to energy performance degradation risks that may affect project revenues and the ability to meet financing obligations. Therefore, project evaluation should consider the interrelationship between technical and financial performance throughout the project lifetime. This study aims to analyze the relationship between energy production degradation, revenue, Cash Flow Available for Debt Service, and debt service capacity over a 25-year operational period of a utility-scale solar PV project. The study employs quantitative financial modeling based on an assumed annual module degradation rate of 0.5%. The relationships among the key parameters are analyzed using a Rational 2D Response Surface model and analysis of variance. The results show that energy production decreases by 11.3% over the 25-year operational period, while revenue declines by 11.4%, operating expenditure increases by 103.5%, and Cash Flow Available for Debt Service decreases by 36.7%. The Rational 2D Response Surface model indicates strong relationships among energy production, revenue, Cash Flow Available for Debt Service, and debt service capacity, with R^2 values exceeding 0.99. These findings demonstrate that reductions in energy production and revenue are accompanied by declines in Cash Flow Available for Debt Service and debt service capacity throughout the operational lifetime of the project. Maintaining the technical performance of solar photovoltaic projects throughout their operational lifetime is essential, as energy production degradation directly affects revenue, Cash Flow Available for Debt Service, and debt service capacity. Quality control from the planning stage through construction is therefore an important component of maintaining the project's financial viability and bankability

KEYWORDS

Financial Performance, Debt Service Capacity, Project Performance, Life-Cycle Performance

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1. INTRODUCTION

Global electricity consumption continues to increase, intensifying concerns about environmental impacts, particularly greenhouse gas emissions such as carbon dioxide (Abolhosseini & Heshmati, 2014). This situation underscores the importance of developing renewable energy as a more sustainable alternative to conventional energy sources, although renewable energy projects generally require higher upfront investments and longer payback periods than fossil-fuel-based power generation (Steffen, 2018). To achieve the objectives of the Paris Agreement, annual

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investment in renewable energy needs to increase substantially, with cumulative investment requirements estimated at approximately USD 16 trillion over the 2015–2050 period. However, investment growth in the electricity sector remains insufficient to meet these targets (Ang et al., 2017). Indonesia has substantial renewable energy potential (Halimatussadiah et al., 2024; Hasudungan & Sabaruddin, 2018; Wong & Dewayanti, 2024), particularly in solar energy, with an estimated potential of 3,294.4 GW. The Indonesian government has targeted a 23% share of renewable energy in the national energy mix by 2025. Through the Electricity Supply Business Plan 2021–2030, the government also planned to develop 20.9 GW of renewable energy capacity, including 4.68 GW of solar power capacity (IRENA, 2020). Despite this substantial potential and policy support, the utilization of renewable energy in Indonesia remains constrained by various challenges, including limited investor understanding of renewable energy resources and their associated investment characteristics (Kasri et al., 2024).

The gap between renewable energy potential and its actual utilization is also reflected in Indonesia's national primary energy supply structure (Diyono et al., 2023). In 2022, Indonesia's primary energy supply reached 327.1 million tonnes of oil equivalent (MTOE), comprising crude oil at 89.2 MTOE (27.27%), natural gas at 73.7 MTOE (22.53%), coal at 112.9 MTOE (34.50%), and new and renewable energy at 51.3 MTOE (15.69%). The National Energy Policy (KEN) and the National Energy Plan (RUEN) (Erdiwansyah et al., 2021; Halimatussadiah et al., 2024) target annual growth in primary energy supply of 7%. However, the realized growth rate was only 4.7%, indicating that increasing energy supply, particularly from renewable sources, continues to face challenges in meeting national targets (Wong & Dewayanti, 2024).

Renewable energy projects are generally capital-intensive, making efficient financing arrangements essential to their successful development. Efficient investment implementation requires the selection of appropriate financing instruments that are aligned with project characteristics and risk profiles (Kalkavan & Eti, 2021). The rapid expansion of large-scale photovoltaic (PV) generation capacity has introduced various investment risks. These include cash flow uncertainty, unreliable supply chains, system component reliability, market distortions, and the qualifications and capabilities of contractors (Kayser, 2016). Such risks may be further compounded by corruption and local protectionism, which can hinder the development of sustainable renewable energy markets (Alberto et al., 2022).

Various policy instruments have been developed to promote renewable energy investment, including feed-in tariffs (FiTs), fiscal incentives, Renewable Portfolio Standards (RPSs), and alternative financing mechanisms supported by waqf and zakat, as well as technological development and regulatory strengthening. Among these instruments, FiTs and fiscal policies have been identified as important mechanisms for attracting renewable energy investment, although their effectiveness depends on policy certainty and prevailing market conditions (Abolhosseini & Heshmati, 2014; Azhgaliyeva et al., 2023; Wall et al., 2019). RPSs and Renewable Energy Certificates (RECs) can also stimulate demand and contribute to the development of more competitive renewable energy markets (Dong, 2012; Sopian et al., 2011). Beyond market-based policies, waqf- and zakat-based financing mechanisms have the potential to expand energy access while generating social and environmental benefits (Ari & Koc, 2021; Karim, 2023) Meanwhile, technological development and infrastructure improvements are necessary to enhance the efficiency and capacity of renewable energy systems (Ari & Koc, 2021; Dong, 2012; Steffen, 2018).

In Indonesia, however, the effectiveness of these policy and financing mechanisms continues to be constrained by regulatory uncertainty, limited financing instruments, and challenges associated with contractual arrangements and renewable energy investment (Burke et al., 2019; Hasudungan & Sabaruddin, 2018; Sopian et al., 2011; Sunarso et al., 2020). These conditions indicate that policy support alone is insufficient to ensure the successful development of renewable energy projects. Financing mechanisms that can reduce investment risks and strengthen project bankability are therefore required. Within a project finance framework, a renewable energy project must demonstrate its ability to generate sufficient cash flows to cover operating costs, meet debt service obligations, and provide an adequate return to investors (Bandaru et al., 2021; Gatti, 2013). A key limitation in the existing literature is the tendency of renewable energy feasibility studies to focus primarily on investment indicators such as Net Present Value (NPV), Internal Rate of Return (IRR), and the levelized cost of electricity (LCOE) (Al Garni et al., 2019; Ariyadi & Purwanto, 2024; Falih et al., 2022). Although these indicators are important for assessing the economic attractiveness of a project, they do not directly indicate whether a project can generate sufficient cash flow to support debt financing. The literature on solar energy project feasibility further emphasizes the need to distinguish between investment profitability indicators and indicators of debt capacity (Bandaru et al., 2021; Lam & Law, 2018; Okoye & Oranekwu-Okoye, 2018)

On the one hand, the Weighted Average Cost of Capital (WACC) is widely used to represent the weighted average cost of equity and debt and is commonly applied as the discount rate in project valuation (Chacko & Padmakumari, 2024; Cifuentes et al., 2025; Guest et al., 2026; Piergallini, 2026; Wildgruber et al., 2026). Changes in WACC, however, affect not only the present value of project cash flows and NPV but also reflect changes in perceived project risk and financing costs. An increase in the cost of capital can therefore reduce financial attractiveness and constrain the project's ability to obtain competitive financing (Wildgruber et al., 2026). Studies on renewable energy investment have identified the cost of capital as a key determinant of project feasibility and investment decisions (Campisi et al., 2018; Lam & Law, 2018; Morea & Poggi, 2017).

In this context, Cash Flow Available for Debt Service (CFADS) provides an important advantage because it translates project operating performance into the cash flow available for debt repayment (Rodríguez, 2024). In solar PV project feasibility analysis, CFADS represents the cash available to service debt and serves as the basis for calculating the Debt Service Coverage Ratio (DSCR). Consequently, changes in energy production, revenue, operating expenditure (OPEX), and taxes can be directly reflected in the project's capacity to meet its financing obligations (Bandaru et al., 2021). However, CFADS is highly sensitive to uncertainty in both technical and financial assumptions. In solar PV projects, in particular, uncertainty in solar resources and energy production can result in cash flow fluctuations and increase the risk of breaching debt covenants (Jadidi et al., 2020; Pacudan, 2016).

Some feasibility studies primarily focus on projected revenues and net cash flows without explicitly distinguishing the portion of project cash flow that is actually available to meet debt service obligations. Within a project finance framework, this component is captured by CFADS, which represents the cash flow available for debt repayment after accounting for relevant project expenditures (Bandaru et al., 2021; Rodríguez, 2024). Debt Service Coverage Ratio (DSCR) is used to assess a project's ability to meet principal and interest payments based on the available CFADS (Alonso-Conde & Rojo-Suárez, 2020; Kurihara et al., 2009; Rodríguez, 2024; Sung & Jung, 2019). In general, DSCR is calculated as the ratio of CFADS to debt service obligations (Bonazzi & Iotti, 2014; Naumenkova et al., 2020).

A higher DSCR indicates a greater capacity to cover debt service obligations and provides a larger cash flow buffer against potential payment risks (Sung & Jung, 2019; Valaskova et al., 2023). Studies of solar energy project feasibility indicate that financial institutions commonly impose minimum DSCR requirements to ensure an adequate cash flow buffer for debt repayment risk (Bandaru et al., 2021; Rodríguez, 2024). In conventional feasibility analysis, however, DSCR is often treated primarily as a compliance indicator against a predetermined threshold. Such an approach does not fully capture the maximum debt service capacity that a project can sustain. By integrating CFADS with a minimum DSCR requirement, the maximum debt service that can be supported by the project's cash flow can be determined for each year of operation. This annual debt service capacity can subsequently be used to estimate the level of debt financing that can theoretically be supported by the project's cash flow.

Previous studies have examined renewable energy investment feasibility using various profitability and financing indicators. However, WACC, CFADS, and DSCR have generally been analyzed separately, leaving the relationship between solar PV energy degradation and production, revenue, cash flow, debt service capacity, and project bankability insufficiently explained from an integrated perspective. This research gap is particularly relevant in Indonesia, where substantial technical solar PV potential does not automatically translate into bankable projects due to the influence of the cost of capital, electricity tariffs, debt structure, financing tenor, and DSCR requirements. An integrated financial model is therefore needed to connect WACC, CFADS, and DSCR with energy production performance in order to assess both the financial feasibility and financing capacity of solar PV projects in Indonesia (Asian Development Bank, 2019; Hasudungan & Sabaruddin, 2018; Kasri et al., 2024; Langer et al., 2023).

The novelty of this study lies in the development of an integrated Response Surface-based model that simultaneously links solar PV energy degradation and production performance with revenue, CFADS, and DSCR. Therefore, this study aims to analyze the relationship between solar PV energy degradation, financial performance, and debt service capacity throughout the project’s operational lifetime using a Life-Cycle Response Surface Approach. The proposed model is designed to capture the dynamic relationships between the degradation of technical asset performance, changes in project cash flows, debt service capacity, and project bankability throughout the operational lifetime of a solar PV project in Indonesia..

2. LITERATURE REVIEW

2.1. Solar Photovoltaic Power

Indonesia has substantial solar energy potential; however, its utilization remains constrained by technical, economic, and financing factors (Azhgaliyeva et al., 2023; Siswantoro & Mahmud, 2023; Sunarso et al., 2020; Ulfah & Al-Kahfi, 2026). Langer et al. (2023) demonstrated that although Indonesia has considerable technical potential for solar photovoltaic (PV) deployment, its bankable potential is substantially lower due to financing risks, electricity tariffs, land availability, and investors' risk perceptions. From a technical perspective, solar PV systems convert solar radiation into direct-current (DC) electricity through photovoltaic cells, while inverters convert DC electricity into alternating-current (AC) electricity for consumption or grid integration.

Advances in PV technology have improved the competitiveness of solar power as a low-emission electricity source, including at the utility scale (Langer et al., 2023). Solar PV projects can be developed as grid-connected systems or integrated with energy storage; however, their economic and financial feasibility is strongly influenced by electricity tariffs, capital costs, technological characteristics, and financing conditions. Paradongan et al. (2024), through a techno-economic assessment of a 26 MW solar PV project in Nias using RETScreen and five tariff scenarios, demonstrated that changes in tariff structures can directly affect project feasibility from the perspectives of both independent power producers (IPPs) and the state-owned utility, PLN. This finding highlights the importance of considering not only the technical performance of solar PV systems but also the economic and contractual conditions under which electricity is generated and sold (Paradongan et al., 2024).

At the utility scale, Langer et al. (2023) incorporated a project finance perspective into the assessment of Indonesia's solar PV potential and found that the estimated technical potential of approximately 12,200 TWh per year substantially exceeds the bankable potential of approximately 16.0 TWh per year under prevailing financing conditions. This substantial gap is associated with financing risks, electricity tariffs, land availability, and the risk perceptions of banks and investors toward solar PV projects (Langer et al., 2023). Similarly, Halimatussadiah et al. (2024), based on interviews with energy-sector stakeholders in Indonesia, identified regulatory uncertainty, limited procurement volumes, unattractive pricing, permitting and land-acquisition challenges, contractual risk allocation, and limited access to project financing as major barriers to renewable energy investment (Halimatussadiah et al., 2024).

These studies collectively indicate that resource availability and technological readiness alone do not guarantee sufficient project cash flows, effective risk allocation, or compliance with project finance requirements. The feasibility of utility-scale solar PV projects therefore depends on the interaction between technical performance and financial conditions throughout the project lifecycle. This perspective underscores the need for financing structures that not only provide the initial capital required for project development but also support long-term financial feasibility and project bankability.

2.2. Cost of Capital and Financial Feasibility in Renewable Energy Projects

Capital is a fundamental component of business operations and value creation (Arofah et al., 2025; Frank & Shen, 2016). One of the key measures used to evaluate the cost of financing is the Weighted Average Cost of Capital (WACC), which represents the weighted average cost of equity and debt based on their respective proportions in the capital structure (Arofah et al., 2025; Cifuentes et al., 2025; Frank & Shen, 2016; Piergallini, 2026). WACC is an important parameter in financial analysis because it is commonly used to evaluate investment profitability and determine the present value of future cash flows. Efficient management of the cost of capital can therefore contribute to improved financial performance and value creation (Arofah et al., 2025; Costa Climent & Haftor, 2021; Huaman-Roque et al., 2025).

Previous studies indicate that WACC is influenced not only by the relative proportions of debt and equity but also by operational characteristics and broader financial conditions. Arofah et al. (2025) emphasized the importance of managing WACC, leverage, liquidity, and asset utilization in improving the financial performance of healthcare companies in Indonesia (Arofah et al., 2025). Yuliah et al. (2023), in their analysis of PT Kalbe Farma Tbk., found that WACC declined during 2018–2021 before increasing by approximately 0.04% in 2022, while the company's financing structure remained more heavily reliant on equity than debt (Yuliah et al., 2023). Similarly, Andrés et al. (2025) demonstrated that WACC estimation in emerging markets requires consideration of capital structure and external financing costs, which are closely associated with firms' financial conditions (Andrés et al., 2025).

The relationship between WACC and value creation is not necessarily linear across different firms and operating conditions. Huaman-Roque et al. (2025) found a relatively strong negative relationship between WACC and Economic Value Added (EVA), with reported WACC values ranging from 3.57% for Backus to 0.27% for Agroindustrias Aib S.A. However, Laive S.A. exhibited a positive relationship between EVA and WACC, suggesting that improvements in operational efficiency and sales growth may offset the adverse effects of higher capital costs (Huaman-Roque et al., 2025). These findings indicate that the effect of WACC on financial value cannot be considered independently of the underlying operational and financial characteristics of the entity being evaluated (Huaman-Roque et al., 2025).

From a project finance perspective, the role of WACC extends beyond its function as a discount rate. Changes in the cost of capital affect the present value of expected project cash flows and consequently influence investment attractiveness and financing feasibility. For capital-intensive renewable energy projects, where substantial upfront investment is required and cash flows are generated over a long operational period, the cost of capital can have a significant effect on project economics. Therefore, an appropriate assessment of financial feasibility requires consideration of both the cost of financing and the project's ability to generate sufficient operating cash flows over time.

Critically, the existing literature has extensively examined WACC in relation to corporate capital structure, financial performance, and value creation. However, WACC is still predominantly analyzed at the corporate level or as a discount rate for project valuation, while its interaction with the operational performance of energy assets and their capacity to generate cash flows for debt repayment remains less explored. In particular, the dynamic relationship between changes in solar PV energy production and the resulting effects on project cash flows, debt service capacity, and financial feasibility has received limited attention. This gap highlights the need to extend the application of WACC beyond a static measure of financing cost toward an integrated framework that connects financing conditions with operational performance and the long-term financial feasibility of utility-scale solar PV projects.

2.3. Cash Flow Available for Debt Service and Debt Repayment Capacity

Cash Flow Available for Debt Service (CFADS) represents the cash flow available to meet a project's debt service obligations over a given period. In solar energy project feasibility analysis, CFADS is generally derived from project revenue after accounting for operating expenditures (OPEX), changes in working capital, taxes, and other relevant cash flow adjustments, while non-cash items such as depreciation are excluded. CFADS subsequently serves as a fundamental measure for assessing a project's ability to meet its debt obligations through the Debt Service Coverage Ratio (DSCR), which is calculated as the ratio of CFADS to scheduled debt service (Arhinful & Radmehr, 2023; Bandaru et al., 2021)

Bandaru et al. (2021) identified CFADS as a relevant financial indicator in renewable energy project feasibility analysis. The formulation of CFADS in their study was based directly on the conceptual framework proposed by Yescombe (2007), which provides a fundamental basis for understanding the cash flow available for debt service in project finance. Within this framework, CFADS represents the project's cash-generating capacity after accounting for operating requirements and relevant financial adjustments, but before the available cash flow is allocated to debt service. Accordingly, Yescombe (2007) and Bandaru et al. (2021) position CFADS as an important link between project operating cash flow and debt repayment capacity (Bandaru et al., 2021; Yescombe, 2007).

The role of CFADS is further reflected in debt service coverage and credit protection metrics, particularly the Debt Service Coverage Ratio (DSCR) and the Loan Life Coverage Ratio (LLCR). Clews (2016), as cited by Bandaru et al. (2021), supports the use of CFADS as the basis for assessing a project's ability to meet debt service obligations through DSCR (Bandaru et al., 2021; Clews, 2016; Rodríguez, 2024). CFADS is also used in the calculation of LLCR, which compares the present value of CFADS expected over the loan life with the outstanding debt balance. These indicators provide complementary perspectives on project debt capacity: DSCR evaluates the project's ability to meet scheduled debt service in a specific period, whereas LLCR assesses the level of cash flow coverage available over the remaining loan life. Thus, the literature establishes CFADS not merely as a measure of project cash flow, but as a fundamental basis for assessing debt repayment capacity and creditor protection through DSCR and LLCR (Ayantokun et al., 2026; Naumenkova et al., 2020; Pacudan, 2016).

Despite its importance in project finance, the existing literature provides limited empirical analysis of the determinants and dynamics of CFADS in renewable energy projects. Bandaru et al. (2021), for example, incorporated CFADS, DSCR, and LLCR into a broader framework of financial indicators. However, in their case study, these indicators were not empirically evaluated as subcriteria for selecting among project alternatives. Instead, the financial assessment was primarily based on capital cost, IRR, payback period, and NPV. Consequently, the study provides stronger conceptual support for the role of CFADS within project finance structures than empirical evidence regarding how changes in project revenue, operating costs, debt structure, or other project risks affect CFADS and debt repayment capacity. For utility-scale solar PV projects, this limitation is particularly relevant because CFADS is directly exposed to changes in energy production and project operating performance throughout the operational lifetime. A decline in energy production can reduce revenue and, consequently, the cash flow available for debt service. Conversely, changes in OPEX, taxation, financing structure, and debt service requirements may further influence the amount of CFADS available to support debt obligations. Therefore, a dynamic assessment of CFADS is necessary to capture how changes in technical performance translate into changes in project cash flow and debt repayment capacity over time.

2.1. Debt Service Coverage Ratio and Debt Service Capacity

The Debt Service Coverage Ratio (DSCR) is widely used to assess a project's ability to meet scheduled debt service obligations, including principal and interest payments, based on the cash flow available for debt service (Ayantokun et al., 2026; Pacudan, 2016; Rodríguez, 2024; Sung & Jung, 2019). Kurihara et al. (2009) explained that a DSCR of 1.0x represents the theoretical minimum threshold, while in practice, lenders may require a higher minimum DSCR, typically ranging from 1.5x to 2.0x depending on project risk. In their biomass project case study, the DSCR reached 2.59x but declined to approximately 1.5x when feedstock availability decreased to 50 tonnes per day and to 1.86x when the project did not receive subsidies.

These findings demonstrate that DSCR is sensitive to both operating conditions and financial support mechanisms (Kurihara et al., 2009). Bonazzi and Iotti (2014) combined DSCR with the Internal Rate of Return on Equity (IRRE) to assess project financial feasibility, with a project considered viable when IRRE exceeded the cost of equity (Ke) and DSCR remained above 1.0x throughout the investment period. In their Italian biogas project case study, this approach demonstrated that the project could maintain financial sustainability despite the use of debt financing. Thus, DSCR was positioned as a financial feasibility criterion rather than merely an additional indicator of project profitability (Bonazzi & Iotti, 2014).

Sung and Jung (2019) examined DSCR from a creditor perspective by comparing Cash Flow Available for Debt Service (CFADS) with debt service consisting of principal and interest payments. Using Monte Carlo simulation, they reported that creditors generally require a minimum DSCR of approximately 1.2–1.5 (Sung & Jung, 2019). Bandaru et al. (2021) similarly positioned DSCR as an indicator of debt repayment capacity based on CFADS. However, its application in their study was primarily conceptual because DSCR was not used as a principal empirical subcriterion in the assessment of the solar project alternatives (Bandaru et al., 2021).

In energy technology applications, Satpute et al. (2025) demonstrated that different PVT configurations can result in different DSCR levels. The zigzag semi-circular absorber configuration achieved a DSCR of 2.1, compared with 1.5 for non-cooled PV and approximately 2.01–2.05 for other PVT configurations (Satpute et al., 2025). Similarly, Ayantokun et al. (2026) used DSCR to compare the financeability of different biogas project configurations. The configuration consisting of 80% fruit and vegetable waste and 20% poultry manure with 100% CHP achieved a minimum DSCR of 2.4. Configurations based on electricity production achieved DSCR values of approximately 2–3, with a first-year DSCR of approximately 2.6, exceeding the infrastructure financing threshold of approximately 1.3–1.5 (Ayantokun et al., 2026).

The studies discussed above demonstrate that DSCR has evolved from a measure of debt payment security into a broader indicator of cash flow sensitivity, financial feasibility, creditor risk, and project bankability. However, the minimum DSCR thresholds reported in the literature vary from above 1.0 to approximately 1.2–1.5 and, in some cases, up to 2.0x or higher. This variation indicates that no single DSCR threshold can be universally applied across all project types and risk profiles. The appropriate threshold depends on factors such as project characteristics, operating uncertainty, financing structure, and lender requirements.

The ratio also reflects the margin of cash flow available to absorb fluctuations in project performance while maintaining debt service. A higher DSCR provides a larger buffer between CFADS and scheduled debt service, whereas a DSCR approaching the minimum threshold indicates greater exposure to cash flow shortfalls. Accordingly, DSCR can be used not only to assess compliance with financing requirements but also to derive the level of debt service that can be supported by the project's available cash flow. This relationship provides an important basis for estimating annual debt service capacity and evaluating the project's ability to sustain debt financing throughout its operational lifetime.

3. METHODOLOGY

3.1. Research Design and Case Study

This study employs a quantitative approach based on financial modelling to evaluate the financial feasibility and debt service capacity of a utility-scale, grid-connected solar photovoltaic (PV) project in Indonesia. Secondary data are used as the research database and comprise technical and financial parameters relevant to the development and operation of the project. The selected parameters are structured to represent the key technical, investment, operational, and revenue characteristics of a utility-scale solar PV project.

The technical parameters include installed capacity, Global Horizontal Irradiance (GHI), annual yield, capacity factor, panel degradation, economic life, and construction period. The financial parameters include capital expenditure (CAPEX), operating expenditure (OPEX), electricity tariff, energy production, cost escalation, financing structure, Sukuk Ijarah yield, and financing tenor. The main project parameters used in the financial model are presented in Table 1.

Table 1. Solar PV Project Parameter Database

Category	Parameter	Value	Unit
Technical	Solar PV capacity	25	MW
	Global Horizontal Irradiance (GHI)	1,691	kWh/m²
	Annual yield	1,352	kWh/kWp
	Capacity factor	17	%
	Panel degradation	0.5	%/year
	Economic life	25	years
	Construction period	12	months
Investment	CAPEX	1,200,000	USD/MW
	Exchange rate	16,2	IDR/USD
	Total CAPEX	486,000,000,000	IDR
Operation	First-year OPEX	2% of CAPEX	IDR/year
	OPEX escalation	3	%/year
Revenue	First-year energy production	37,23	MWh/year
	Production degradation	0.5	%/year
	Electricity	25	IDR/kWh

Source: : (Al Garni et al., 2019; Al Garni & Awasthi, 2017; Ariyadi & Purwanto, 2024; Falih et al., 2022; IRENA, 2020; Langer et al., 2023; Paradongan et al., 2024) compiled by the authors, 2026

The parameters in Table 1 are subsequently used to construct the baseline financial model. Annual energy production is determined based on the installed capacity, annual yield, and panel degradation rate. Revenue is then calculated from annual electricity production and the applicable electricity tariff. Meanwhile, CAPEX represents the initial investment requirement, while OPEX represents the recurring operating costs throughout the project's operational period.

The baseline model provides the foundation for the subsequent financial analysis, including the estimation of project cash flows, Cash Flow Available for Debt Service (CFADS), Debt Service Coverage Ratio (DSCR), and annual debt service capacity. The model is evaluated over the project's 25-year economic life to capture the effects of changes in technical performance and operating costs on the project's long-term financial performance and debt repayment capacity.

3.2. Variables and Model Inputs

This study employs technical and financial variables to construct the baseline financial model of the solar PV project. The outputs of the baseline model are subsequently used as variables in the Response Surface analysis.

The project operating year is incorporated as a time variable to capture the dynamic relationships between technical performance and financial indicators throughout the project's operational lifetime. The structure of the variables and model inputs used in the analysis is presented in Table 2.

Table 2. Variables and Model Inputs in the Solar PV Project Analysis

Analysis Stage	Relationship Model	Independent Variables	Time Variable	Response Variable
Baseline Model	Energy Production	Capacity, GHI, Annual Yield, Capacity Factor, Panel Degradation	Operating Year (t)	Energy Production (MWh)
Baseline Financial Model	Financial Performance	CAPEX, OPEX, Electricity Tariff, Financing Structure, Cost Escalation	Operating Year (t)	Revenue, Taxes, CFADS, DSCR_{max}
Response Surface I	CFADS–Revenue	CFADS (IDR)	Operating Year (t)	Revenue (IDR)
Response Surface II	Energy Production–CFADS	Energy Production (MWh)	Operating Year (t)	CFADS (IDR)
Response Surface III	DSCR_{max}–Revenue	DSCR_{max} (IDR)	Operating Year (t)	Revenue (IDR)
Response Surface IV	Energy Production–DSCR_{max}	Energy Production (MWh)	Operating Year (t)	DSCR_{max}

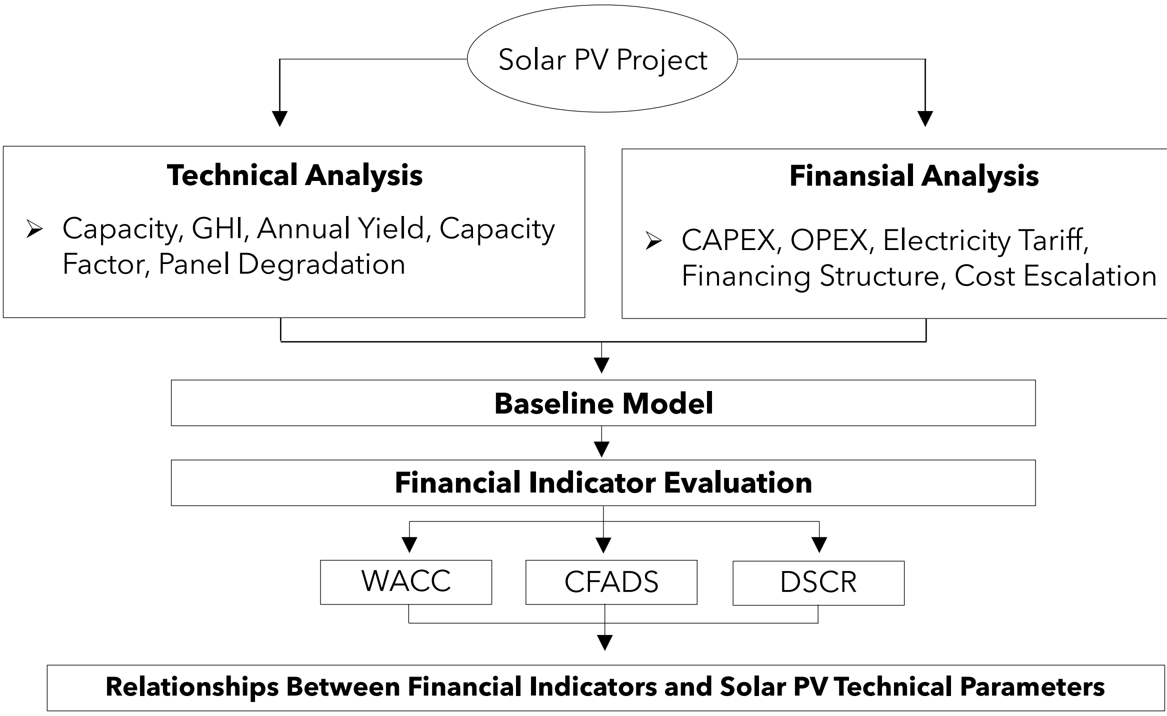


Figure 1. Design Methodology

Figure 1 show methodological framework of the study. The analysis begins with the identification of the technical and financial parameters of the solar PV project. The selected parameters are then incorporated into the baseline financial model to project the project's technical performance and cash flows throughout the operational period. The resulting model outputs are subsequently evaluated using key financial indicators, including the Weighted Average Cost of Capital (WACC), Cash Flow Available for Debt Service (CFADS), and Debt Service Coverage Ratio (DSCR). These indicators are then used to examine the relationships between the project's technical parameters and financial performance over its operational lifetime.

3.3. Annual Energy Production

The annual energy production of the solar PV project is projected based on the installed capacity, the number of hours in a year, the capacity factor, and the annual module degradation rate. In the baseline model, the first-year energy production is calculated using an installed solar PV capacity of 25 MW, an annual operating period of 8,760 hours, and a capacity factor of 17%. The energy production in subsequent years is adjusted using a module degradation rate of 0.5% per year. The annual energy production for each operating year is calculated using Eq.1. The results presented in Table 3.

$$E_t = C \,.\, H \,.\, CF \,.\, (1-d)^{t-1} \tag{1}$$

Where E_t is the annual energy production in year (t) (MWh/year), (P) is the installed solar PV capacity (MW), (H) is the number of hours in a year (h/year), (CF) is the capacity factor, (d) is the annual module degradation rate, and (t) is the operating year of the project.

Table 3. Annual Energy Production Projection of the Solar PV Project

Year (t)	Degradation Factor		Energy Production (MWh/year) (E_t)
1	$(1 - 0.005)^0$	1	37,230 MWh
2	$(1 - 0.005)^1$	0.995	37,044 MWh
3	$(1 - 0.005)^2$	0.99	36,859 MWh
4	$(1 - 0.005)^3$	0.9851	36,674 MWh

5	$(1 - 0.005)^{4}$	0.9801	36,491 MWh
6	$(1 - 0.005)^{5}$	0.9752	36,309 MWh
7	$(1 - 0.005)^{6}$	0.9704	36,127 MWh
8	$(1 - 0.005)^{7}$	0.9655	35,946 MWh
9	$(1 - 0.005)^{8}$	0.9607	35,767 MWh
10	$(1 - 0.005)^{9}$	0.9559	35,588 MWh
11	$(1 - 0.005)^{10}$	0.9511	35,410 MWh
12	$(1 - 0.005)^{11}$	0.9464	35,233 MWh
13	$(1 - 0.005)^{12}$	0.9416	35,057 MWh
14	$(1 - 0.005)^{13}$	0.9369	34,881 MWh
15	$(1 - 0.005)^{14}$	0.9322	34,707 MWh
16	$(1 - 0.005)^{15}$	0.9276	34,533 MWh
17	$(1 - 0.005)^{16}$	0.9229	34,361 MWh
18	$(1 - 0.005)^{17}$	0.9183	34,189 MWh
19	$(1 - 0.005)^{18}$	0.9137	34,018 MWh
20	$(1 - 0.005)^{19}$	0.9092	33,848 MWh
21	$(1 - 0.005)^{20}$	0.9046	33,679 MWh
22	$(1 - 0.005)^{21}$	0.9001	33,510 MWh
23	$(1 - 0.005)^{22}$	0.8956	33,343 MWh
24	$(1 - 0.005)^{23}$	0.8911	33,176 MWh
25	$(1 - 0.005)^{24}$	0.8867	33,010 MWh

Table 3 shows a gradual decline in the energy production of the solar PV project throughout its operational lifetime due to the application of a module degradation rate of 0.5% per year. Energy production in the first year is 37,230 MWh and is projected to decline to 33,010 MWh in the 25th year.

3.4. Baseline Financial Model

Financial feasibility and project bankability are evaluated using the Weighted Average Cost of Capital (WACC), Cash Flow Available for Debt Service (CFADS), and Debt Service Coverage Ratio (DSCR) to assess the project's ability to meet its financing obligations, as well as the cost of electricity generation (Bandaru et al., 2021; Gatti, 2013; Steffen, 2018). WACC is used as the weighted average cost of capital that represents the project's financing structure. The WACC calculation combines the cost of equity and the after tax cost of debt based on the respective proportions of equity and financing in the capital structure. WACC is calculated using Eq.2

$$WACC = \left(\frac{E}{D+E}.R_e\right) + \left(\frac{D}{D+E}.R_d.(1-T)\right) \tag{2}$$

where (E) is total equity, (D) is debt financing, (R_e) is the cost of equity, (R_d) is the pre tax cost of debt, and (t) is the tax rate. The cost of equity is calculated using the Capital Asset Pricing Model (CAPM) adjusted for country risk through the country risk premium, as presented in Eq. 3

$$R_e = R_f + \beta + (R_m - R_f) + CRP \tag{3}$$

where R_e is the Cost of Equity, R_f is Risk-free rate, β is the project beta, $R_m - R_f$ is the equity risk premium, and (CRP) is the country risk premium. The after tax cost of debt is then calculated where $R_d(1-T)$. Where R_d a is the pre tax cost of debt and (t) is the tax rate. The resulting WACC values for the conventional and Sukuk Ijarah financing schemes are presented in the following table 4

Table 4. Comparative WACC Assumptions for Conventional and Sukuk Ijarah Financing Schemes

Component	Conventional Scheme	Sukuk Ijarah Scheme
Capital Structure		
Debt to Total Capitalization	70.00%	70.00%
Equity to Total Capitalization	30.00%	30.00%
Cost of Equity Calculation		
Risk-free Rate (R_f)	6.19%	6.19%
Equity Risk Premium ($R_m - R_f$)	6.87%	6.87%
Country Risk Premium (CRP)	2.54%	2.54%
Beta (β)	1	1
Cost of Equity (R_e)	15.60%	15.60%
Cost of Debt Calculation		
Pre-tax Cost of Debt	8.80%	7.00%
Tax Rate (T)	22.00%	22.00%
After-tax Cost of Debt	6.86%	5.46%
WACC	9.48%	8.50%

Table 4 shows that the capital structure used in both financing schemes is assumed to be the same, consisting of 70% debt financing and 30% equity. The parameters used to calculate the cost of equity are also identical for both schemes, with a risk free rate of 6.19%, an equity risk premium of 6.87%, a country risk premium of 2.54%, and a beta value of 1.00.

Based on these parameters, the cost of equity is 15.60% for both financing schemes. The main difference between the two financing schemes is the cost of debt. Under the conventional scheme, the pre tax cost of debt is 8.80%, whereas the Sukuk Ijarah scheme has a pre tax financing cost of 7.00%. Considering a tax rate of 22%, the resulting after tax cost of debt is 6.86% and 5.46%, respectively. These differences in financing costs result in a WACC of 9.48% for the conventional scheme and 8.50% for the Sukuk Ijarah scheme. Thus, the WACC under the Sukuk Ijarah scheme is 0.98 percentage points lower than that under the conventional financing scheme. Subsequently, CFADS is calculated based on electricity sales revenue after deducting operation and maintenance costs and income tax.

Depreciation is not directly deducted in the calculation of CFADS because it is a non cash expense; however, it is used to determine taxable income and the corresponding income tax. The first year CFADS is calculated from electricity revenue less OPEX and income tax, as presented in Eq. 4

$$CFADS_t = R_t - OPEX_t - Tax_t \tag{4}$$

Income tax is calculated based on taxable income using Eq.5

$$Tax_t = (R_t - OPEX_t - Dept_t)\,.T \tag{5}$$

Then, substituting Eq. 4 into Eq. 5, the CFADS calculation show Eq. 6

$$CFADS_t = R_t - OPEX_t - [((R_t - OPEX_t - Dept_t)]\,.T \tag{6}$$

where $CFADS_t$ is the Cash Flow Available for Debt Service in year (t), $Revenue_t$ is project revenue in year (t), $OPEX_t$ is operation and maintenance expenditure in year (t), Tax_t is income tax in year (t), $Dept_t$ is depreciation expense in year (t), (T) is the income tax rate, and (t) is the operating year of the project. In this study, the income tax rate is set at 22%, while project depreciation is calculated at IDR 19,440,000,000 per year over the project's economic life. This depreciation value is used to determine taxable income before calculating income tax. The projected CFADS for each operating year, from (t=1) to (t=25), is presented in Table 5

Table 5. Cash Flow Available for Debt Service (CFADS)

Year ***(t)***	**Revenue** ***(IDR)***	**OPEX** ***(IDR)***	**Depreciation** ***(IDR)***	**Income Tax** ***(IDR)***	**CFADS** ***(IDR)***
1	45,727,747,500	9,720,000,000	19,440,000,000	3,644,904,450	32,362,843,050
2	45,499,108,763	10,011,600,000	19,440,000,000	3,530,451,928	31,957,056,835
3	45,271,613,219	10,311,948,000	19,440,000,000	3,414,326,348	31,545,338,871
4	45,045,255,153	10,621,306,440	19,440,000,000	3,296,468,717	31,127,479,996
5	44,820,028,877	10,939,945,633	19,440,000,000	3,176,818,314	30,703,264,930
6	44,595,928,732	11,268,144,002	19,440,000,000	3,055,312,641	30,272,472,090
7	44,372,949,089	11,606,188,322	19,440,000,000	2,931,887,369	29,834,873,398
8	44,151,084,343	11,954,373,972	19,440,000,000	2,806,476,282	29,390,234,090
9	43,930,328,922	12,313,005,191	19,440,000,000	2,679,011,221	28,938,312,510
10	43,710,677,277	12,682,395,347	19,440,000,000	2,549,422,025	28,478,859,906
11	43,492,123,891	13,062,867,207	19,440,000,000	2,417,636,470	28,011,620,213
12	43,274,663,271	13,454,753,223	19,440,000,000	2,283,580,211	27,536,329,837
13	43,058,289,955	13,858,395,820	19,440,000,000	2,147,176,710	27,052,717,425
14	42,842,998,505	14,274,147,695	19,440,000,000	2,008,347,178	26,560,503,632
15	42,628,783,513	14,702,372,126	19,440,000,000	1,867,010,505	26,059,400,882
16	42,415,639,595	15,143,443,289	19,440,000,000	1,723,083,187	25,549,113,118
17	42,203,561,397	15,597,746,588	19,440,000,000	1,576,479,258	25,029,335,551
18	41,992,543,590	16,065,678,986	19,440,000,000	1,427,110,213	24,499,754,391
19	41,782,580,872	16,547,649,355	19,440,000,000	1,274,884,934	23,960,046,583
20	41,573,667,968	17,044,078,836	19,440,000,000	1,119,709,609	23,409,879,523
21	41,365,799,628	17,555,401,201	19,440,000,000	961,487,654	22,848,910,773
22	41,158,970,630	18,082,063,237	19,440,000,000	800,119,626	22,276,787,766
23	40,953,175,777	18,624,525,134	19,440,000,000	635,503,141	21,693,147,501
24	40,748,409,898	19,183,260,888	19,440,000,000	467,532,782	21,097,616,227
25	40,544,667,848	19,758,758,715	19,440,000,000	296,100,009	20,489,809,124

Table 5 shows that the project's CFADS gradually decreases throughout the operational period, from IDR 32.36 billion in the first year to IDR 20.49 billion in the 25th year. This reduction results from the decline in revenue due to energy production degradation and the increase in OPEX over the project's operational lifetime.

The resulting CFADS is subsequently used as the basis for determining the DSCR and the maximum debt service capacity (Debt Service Maximum). In this study, the Debt Service Maximum is calculated by dividing annual CFADS by the minimum DSCR threshold of 1.25. Thus, the Debt Service Maximum represents the maximum annual debt service obligation that can be supported by the project's available cash flow while maintaining the minimum cash flow coverage specified in the model. The Debt Service Maximum in year (t) is calculated using Eq. 7

$$DS_{Max,t} = \frac{CFADS_t}{DSCR_{min}} \tag{7}$$

where $DS_{Max,t}$ is Debt Service Maksimum in year (t), $CFADS_t$ is Cash Flow Available for Debt Service in year (t), and $DSCR_{min}$ is the minimum Debt Service Coverage Ratio threshold. The calculated Debt Service Maximum values for years 1 to 25 are presented in Table 6

Table 6. Cash Flow Available for Debt Service (CFADS)

Year ***(t)***	**CFADS** ***(IDR)***	**$DSCR_{min}$**	**$DSCR_{max}$**
1	32,362,843,050	1.25	25,890,274,440
2	31,957,056,835	1.25	25,565,645,468
3	31,545,338,871	1.25	25,236,271,096
4	31,127,479,996	1.25	24,901,983,997
5	30,703,264,930	1.25	24,562,611,944
6	30,272,472,090	1.25	24,217,977,672
7	29,834,873,398	1.25	23,867,898,718
8	29,390,234,090	1.25	23,512,187,272
9	28,938,312,510	1.25	23,150,650,008
10	28,478,859,906	1.25	22,783,087,924
11	28,011,620,213	1.25	22,409,296,170
12	27,536,329,837	1.25	22,029,063,870
13	27,052,717,425	1.25	21,642,173,940
14	26,560,503,632	1.25	21,248,402,906
15	26,059,400,882	1.25	20,847,520,705
16	25,549,113,118	1.25	20,439,290,495
17	25,029,335,551	1.25	20,023,468,441
18	24,499,754,391	1.25	19,599,803,513
19	23,960,046,583	1.25	19,168,037,266
20	23,409,879,523	1.25	18,727,903,618
21	22,848,910,773	1.25	18,279,128,618
22	22,276,787,766	1.25	17,821,430,213
23	21,693,147,501	1.25	17,354,518,001
24	21,097,616,227	1.25	16,878,092,982
25	20,489,809,124	1.25	16,391,847,299

Table 6 shows that the Debt Service Maximum gradually decreases from IDR 25,890,274,440 in the first year to IDR 16,391,847,299 in the 25th year. This change follows the decline in the project's CFADS throughout the operational period. By maintaining a minimum DSCR of 1.25, each Debt Service Maximum value represents the highest debt service obligation that can be supported by the project in each year without violating the minimum debt service coverage requirement.

The annual Debt Service Maximum is discounted to obtain the present value of the project's debt service capacity under different financing tenor alternatives. Therefore, the Debt Service Maximum serves as a link between the project's operating cash flow capacity, DSCR requirements, and the determination of the financing amount that can be supported by the project.

3.5. Response Surface Analysis

Response Surface Analysis is a statistical method used to model the relationship between input variables and response variables, allowing the identification and evaluation of optimal conditions within a model (Badri et al., 2022; Manojkumar et al., 2022; Setyorini et al., 2026). The experimental design, model development, and analysis of variance (ANOVA) are conducted using OriginLab 2024 (Version 10.1). The modelling scenarios are evaluated using a multivariate meta-model through Rational 2D regression, as presented in Eq. 8

$$z = \frac{z_0+A_{01}x+B_{01}y+B_{02}y^2+B_{03}y^3}{1+A_1x+A_2x^2+A_3x^3+B_1y+B_2y^2} \tag{8}$$

In this model, (z) represents the response variable, while z0 represents the baseline model constant. The variable (x) represents the operating year, with (x=1) to (25), while (y) represents the corresponding input parameter from the financial baseline model. The coefficients in the numerator (A_{01}, B_{01}, B_{02}, dan B_{03}) represent the linear to nonlinear effects of the variables being analyzed, while the coefficients in the denominator (A_1, A_2, A_3, B_1, dan B_2) represent the linear, quadratic, and cubic contributions to the model response. This equation structure is used to simultaneously evaluate the relationship between the financial model and the technical energy requirements of the solar PV project in Indonesia.

4. RESULTS AND DISCUSSION

4.1. Degradation Factor and Energy Production

The relationship between the module degradation factor and annual energy production is analyzed to describe changes in the performance of the solar PV project throughout its operational lifetime. The analysis covers the period from the first year to the 25th year of operation, with the results presented in Figure 2 and Table 7

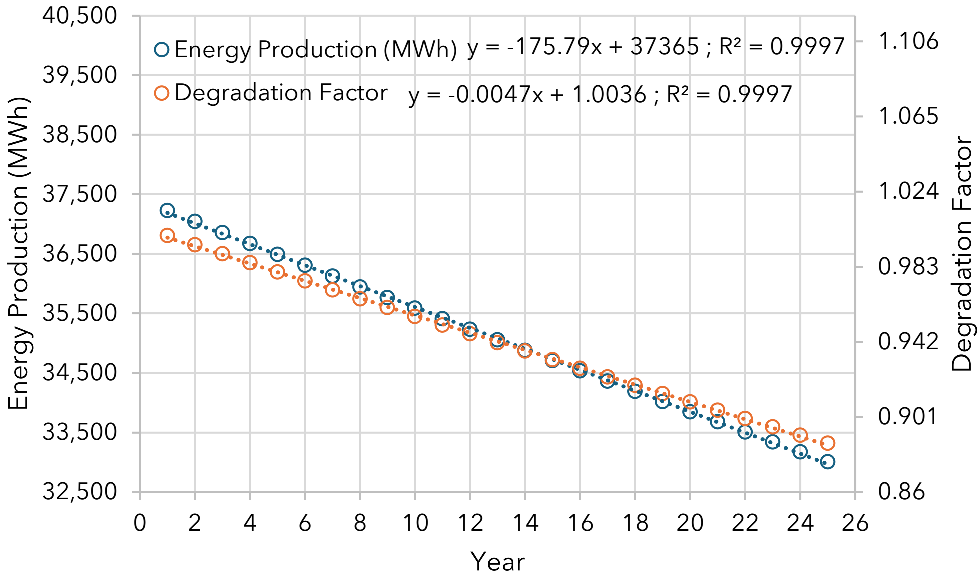


Figure 2. Relationship Between Annual Energy Production and Operating Year of the Solar PV Project

Figure 2 shows the relationship between the annual energy production of the solar PV project and the degradation factor throughout the operational period. The projection results show that energy production decreases consistently from approximately 37,230 MWh in the first year to approximately 33,010 MWh in the 25th year.

This reduction follows the assumed module degradation rate of 0.5% per year, which is consistent with commonly adopted degradation assumptions in financial models for crystalline silicon PV projects (Pascual et al., 2021). Similar field evidence from tropical conditions in Thailand reported degradation rates ranging from 0.5% to 4.9% per year and confirmed that degradation can substantially reduce PV output over a 25-year lifetime (Limmanee et al., 2016).

The relationship between the two parameters exhibits a very strong linear pattern, with a coefficient of determination of $R^2 = 0.9997$. Furthermore, Table 7 presents the parameters of the linear equations used to describe the development of energy production and the degradation factor over time. The equations show that operating year is the primary variable explaining the changes in both parameters.

The negative coefficient in the energy production equation represents the decline in energy output throughout the operational lifetime, while the degradation factor also decreases progressively as the project ages.

Table 7. Degradation and Energy Production Parameters over the Operating Period

Parameter	Equation Value $y = a_x + b$	R^2
Energy Production (MWh)	y = -175.79x + 37365	0.9997
Degradation Factor	y = −0.0047x + 1.0036	0.9997

The relationship is represented by the linear model summarized in Table 7. In these equations, (y) represents the respective energy production or degradation factor parameter, while (x) represents the operating year of the project. The negative coefficient in the energy production equation indicates that energy output decreases by approximately 176 MWh per year under the linear trend observed during the analysis period. Meanwhile, the coefficient of (-0.0047x) in the degradation factor equation represents a consistent reduction in system performance as the operating period increases.

The R^2 value of 0.9997 indicates a very strong relationship between operating year and changes in both parameters, demonstrating that the observed decline in energy production can be consistently represented by the model over the analyzed period. The degradation factor should therefore be considered from the project planning stage and incorporated into the assessment of life cycle performance.

The cumulative reduction in energy production can affect revenue projections, operating and maintenance requirements, and the project's available cash flow. Accordingly, the quality management of module procurement, installation quality control, maintenance strategies, and component replacement planning are important factors in maintaining energy performance in accordance with the initial project projections.

The success of a solar PV project is not determined solely by completing construction within the planned cost and schedule, but also by the ability of decisions made during the planning, procurement, and construction stages to maintain asset performance throughout its service life. The strong relationship between degradation and energy production shown in Figure 2 indicates that deviations in asset performance have the potential to translate directly into deviations in project revenue and financial performance.

4.2. Baseline Financial Performance and Life-Cycle Cash Flow Dynamics

Project financial performance is analyzed based on the development of revenue, operating expenditure (OPEX), taxes, and Cash Flow Available for Debt Service (CFADS) throughout the operational period. Changes in each parameter are analyzed against the operating year to identify the baseline pattern of the project's cash flow.

The results are presented in Fig. 3 and Table 8 below.

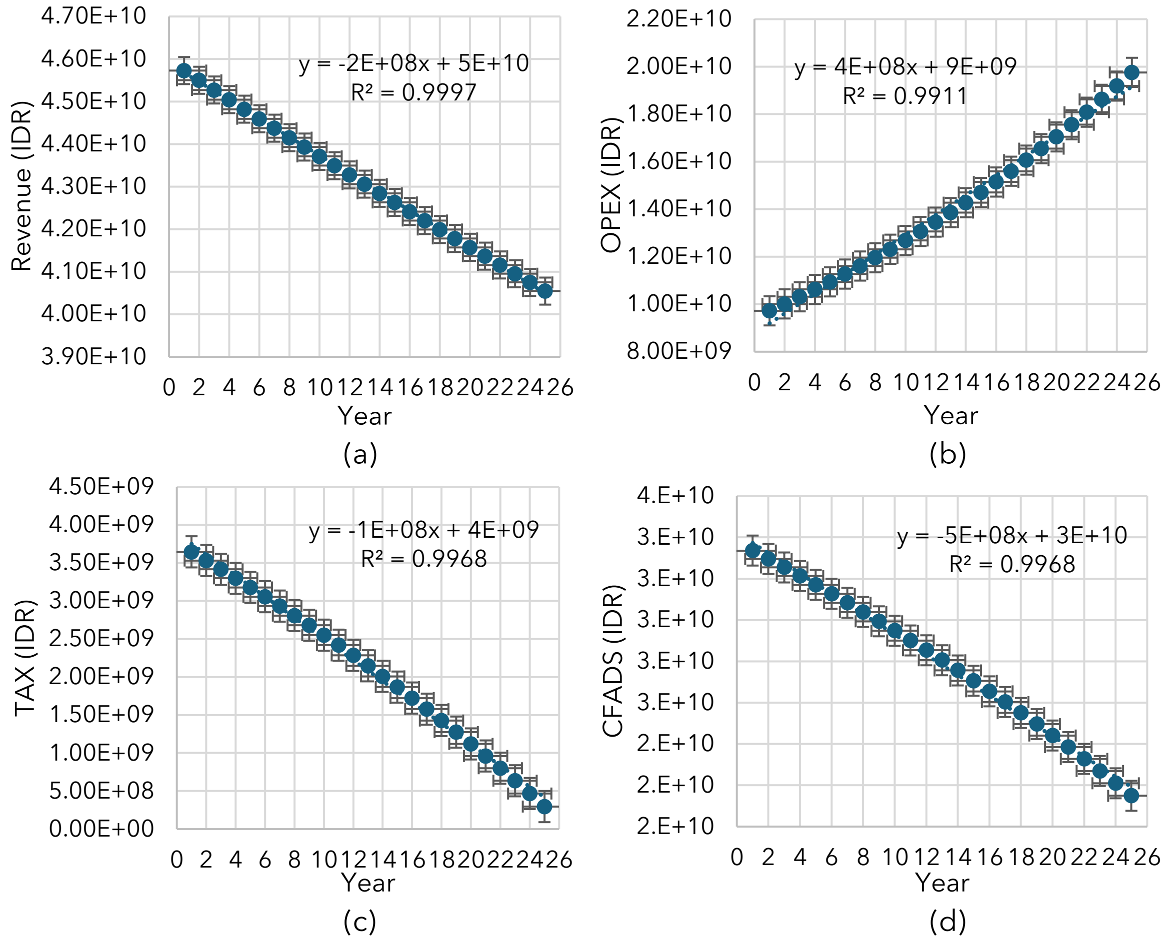


Figure 3. Baseline Financial (IDR) Model. (a) Revenue; (b) OPEX; (c) TAX; (d) CFADS

Figure 3 shows that *revenue*, taxes, and Cash Flow Available for Debt Service (CFADS) exhibit declining trends, whereas operating expenditure (OPEX) increases progressively throughout the operational period. Revenue decreases from approximately IDR 45.7 billion to IDR 40.5 billion, while OPEX increases from approximately IDR 9.7 billion to IDR 19.8 billion. The combination of these changes results in a decline in CFADS from approximately IDR 32.4 billion in the first year to IDR 20.5 billion in the 25th year.

Table 7. Baseline Financial Model Parameters over the Operating Period

Parameter (IDR)	Equation Value	R^2
Revenue	y = -2E+08x + 5E+10	0.9997
OPEX	y = 4E+08x + 9E+09	0.9911
TAX	y = -1E+08x + 4E+09	0.9968
CFADS	y = -5E+08x + 3E+10	0.9968

The relationships are represented by the linear models summarized in Table 7. In these equations, (y) represents the respective financial parameter being analyzed, while (x) represents the operating year of the project. The coefficients indicate the direction and magnitude of the change in each parameter over time. The negative coefficient in the revenue equation indicates a decline in revenue of approximately IDR 200 million per year, whereas the positive coefficient for OPEX indicates an increase in operating costs of approximately IDR 400 million per year.

At the same time, tax and CFADS have negative coefficients, indicating that the decline in the project's available cash flow is primarily associated with decreasing revenue and increasing operating costs. This relationship is consistent with previous solar PV feasibility studies, which identify revenue, OPEX, and CFADS as key components of project cash flow and DSCR assessment (Bandaru et al., 2021; Imasiku, 2021). The coefficients of determination, with R^2 values ranging from 0.9911 to 0.9997, demonstrate a very strong relationship between all financial parameters and the operating year. Revenue exhibits the highest model fit, with $R^2 = 0.9997$, while OPEX also shows a very strong temporal pattern, with $R^2 = 0.9911$.

These results demonstrate that the project's financial risk is not determined solely by the initial investment cost, but also by the ability of decisions made during project planning and implementation to maintain asset performance throughout its life cycle.

Previous research also emphasizes that long-term PV financial performance depends on maintaining reliable energy production and controlling operating costs because project cash flows support debt repayment and financing obligations (Firouzi & Meshkani, 2021).

The decline in energy production, which reduces revenue, together with the increase in OPEX, directly reduces CFADS and the project's capacity to meet its financing obligations. In this case, deviations in asset quality or performance that increase maintenance requirements or accelerate production degradation can directly translate into lower CFADS and reduced debt service capacity. Therefore, project success should not be assessed solely based on cost, schedule, and quality performance during the construction stage, but also on the ability of construction-related decisions to maintain the asset's life-cycle cash flow throughout the operational period.

4.3. Life-Cycle Energy Performance and Financial Implications

The relationship between financial characteristics and energy production is analyzed using the Rational 2D Response Surface model based on the progression of operating years.

This model is used to describe the simultaneous response between the parameters and changes in their values throughout the project's operational period. The modelling results are presented in Figure 4 and Table 8

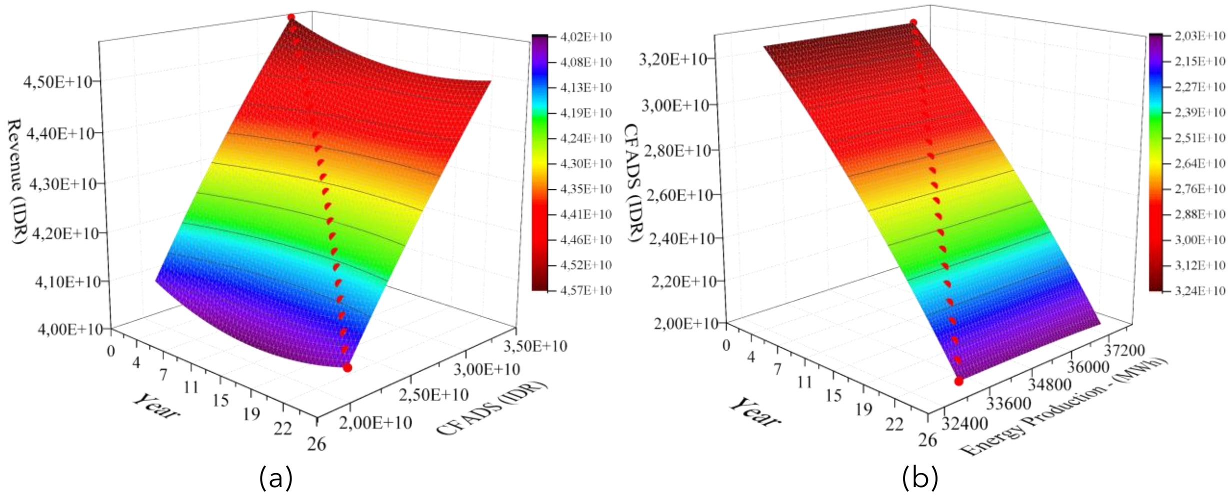


Figure 4. Relationship between CFADS (IDR) and Revenue (IDR), and Energy Production (MWh) and CFADS (IDR), over the Operating Period. (a) CFADS–Revenue; (b) Energy Production–CFADS

Figure 4 shows the response surfaces between the analyzed parameters and the progression of operating years. Figure 4(a) illustrates the simultaneous relationship between CFADS and revenue, whereas Figure 4(b) shows the relationship between energy production and CFADS.

The color transition from red to blue represents a decrease in the response value. Thus, the color gradients across both surfaces provide a visual representation of the financial and operational performance characteristics throughout the project period.

Table 8. Parameters of the Regression Model Based on the Response Relationships

Regression coefficient				ANOVA				Statistic		
Var.	Coefficient value	t-Value	Prob>|t|	Sum of Squares	Mean Square	F Value	Prob>F	Reduced Chi-Sqr	Residual Sum of Squares	R^2
CFADS (IDR) & Revenue (IDR)										
z_0	5.98E+10	4.88E-06	1.00E+00	1.83E+22	1.83E+21	6.87E+04	<0.0001	2.66E+16	4.00E+17	0.9987
A_{01}	-1.62E+11	-4.46E-03	9.97E-01							
B_{01}	-5.49E+01	-1.20E-04	1.00E+00							
B_{02}	1.23E-08	2.61E-03	9.98E-01							
B_{03}	-2.20E-19	-6.63E-03	9.95E-01							
A_1	-1.81E+00	-3.96E-03	9.97E-01							
A_2	-9.92E-04	-2.06E-03	9.98E-01							
A_3	-2.55E-03	-4.82E-03	9.96E-01							
B_1	7.88E-10	1.65E-03	9.99E-01							
B_2	1.60E-20	4.34E-03	9.97E-01							
Energy Production (MWh) & CFADS (IDR)										
z_0	5.04E+03	3.18E-04	1.00E+00	3.08E+10	3.08E+09	3.14E+10	<0.0001	9.82E-02	1.47E+00	0.9958
A_{01}	4.46E+02	9.76E-04	9.99E-01							
B_{01}	1.10E-06	7.80E-03	9.94E-01							
B_{02}	-5.69E-18	-9.98E-04	9.99E-01							
B_{03}	3.06E-28	3.73E-03	9.97E-01							
A_1	6.60E-04	1.17E-04	1.00E+00							
A_2	-1.21E-05	-2.56E-03	9.98E-01							
A_3	-2.53E-07	-1.02E-03	9.99E-01							
B_1	1.14E-11	1.18E-03	9.99E-01							
B_2	-1.44E-22	-7.99E-04	9.99E-01							

Table 8 shows that the model describing the relationship between CFADS and revenue achieves an R^2 of 0.99874, while the relationship between energy production and CFADS achieves an R^2 of 0.9958. Both values indicate a high degree of model fit for the respective response relationships. For the relationship of CFADS–revenue, coefficients A_{01} = -1.62E+11, B_{01} = -5.49E+01, dan A_1 = -1.81E+00 indicate a declining response with the progression of operating years. Meanwhile, the coefficients A_2 = -9.92E-04 and A_3 = -2.55E-03 further contribute to the curvature of the response surface.

The combined effects produce a gradient from the red zone, representing higher response values, toward the blue zone, representing lower response values. The very small interaction coefficients B_1 = 7.88E-10 and B_2 = 1.60E-20 suggest that the overall surface pattern is dominated by the underlying trend rather than nonlinear interaction effects.

For the energy production–CFADS relationship, the positive coefficients A_{01} = 4.46E+02, B_{01} =1.10E-06, and A_1 = 6.60E-04 contribute to the higher initial response level, visually represented by the red to yellow zones of the surface. In contrast, the negative coefficients B_{02} = -5.69E-18, A_2 = -1.21E-05, A_3 = -2.53E-07 and B_2 = -1.44E-22, contribute to the declining response toward the green, blue, and purple zones. Meanwhile, the positive coefficients B_{03} = 3.06E-28 and B_1 = 1.10E-06, have relatively small contributions to the curvature of the surface.

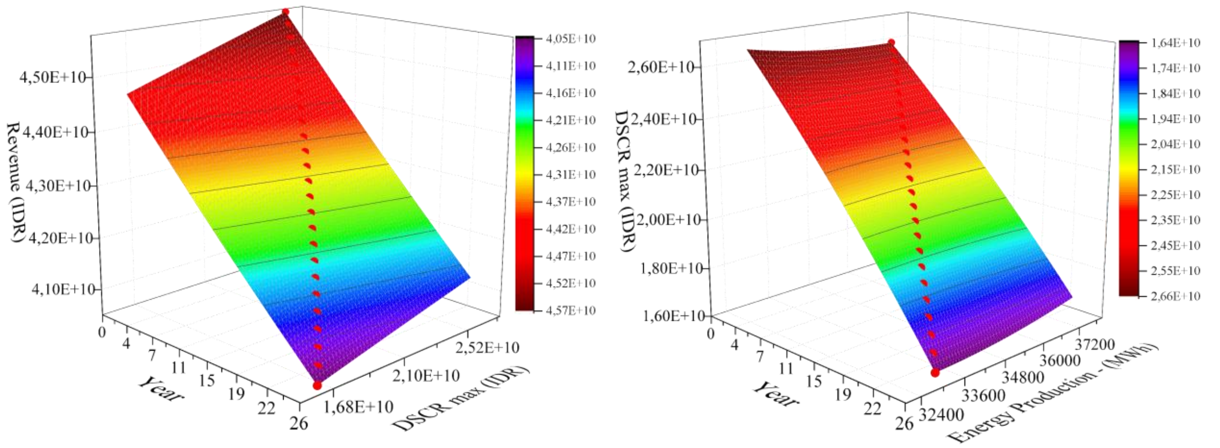
The combination of these coefficients produces a response gradient that represents the decline in CFADS associated with changes in energy production and the progression of the operational period. This finding is consistent with previous solar PV project finance studies showing that changes in energy production and project cash flow can directly affect financing capacity and DSCR. Pacudan (2016) demonstrated that variations in solar energy production influence the financing performance of a utility-scale PV project, while Firouzi and Meshkani (2021) showed that changes in revenue and free cash flow are directly relevant to debt service scheduling in a solar PV project (Firouzi & Meshkani, 2021; Pacudan, 2016).

The response patterns demonstrate the relationship between the technical performance of the asset and the project's financial capacity. A decline in energy production does not remain limited to a reduction in operational output but is translated into lower revenue and CFADS. Therefore, construction decisions related to installation quality, component selection, quality control, and maintenance strategies should be considered as determinants of life-cycle performance, rather than merely activities for achieving construction cost, quality, and schedule targets.

The transition in response surface colors from red to blue illustrates the decline in project value over the operational lifetime, highlighting the importance of controlling asset performance from the construction stage to maintain project cash flow and financing capacity.

4.4. Energy Production and Revenue Effects on Debt-Service Capacity

Relationship between debt service capacity, revenue, and energy production is analyzed using the Rational 2D Response Surface model over the operating years. The model is used to describe the simultaneous changes in debt service capacity with respect to revenue and energy production throughout the project's operational period.



(a) (b)

Figure 5. Relationship between Debt Service Maximum (IDR) and Operating Period. (a) Debt Service Maximum (IDR) & Revenue (IDR); (b) Energy Production (MWh) & Debt Service Maximum (IDR

Figure 5 shows that the Debt Service Maximum exhibits a declining response over the operational period, both in relation to revenue and energy production. The transition from red to blue represents a change from higher response values to lower response values.

Table 9. Parameters of the Regression Model Based on the Response Relationships

Regression coefficient				ANOVA				Statistic		
Var.	Coefficient value	t-Value	Prob>|t|	Sum of Squares	Mean Square	F Value	Prob>F	Reduced Chi-Sqr	Residual Sum of Squares	R^2
$DSCR_{max}$ (IDR) & Revenue (IDR)										
z_0	9.17E+10	1.93E-01	8.49E-01	1.17E+22	1.17E+21	1.43E+13	<0.0001	8.22E+07	1.23E+09	0.9978
A_{01}	8.92E+09	2.41E+00	2.93E-02							
B_{01}	-5.48E+01	-8.26E+00	5.83E-07							
B_{02}	5.87E-10	1.79E+00	9.43E-02							
B_{03}	1.47E-20	2.38E+00	3.09E-02							
A_1	-2.96E-01	-5.33E+00	8.38E-05							
A_2	3.44E-03	1.29E+01	1.59E-09							
A_3	-1.23E-05	-5.35E+00	8.10E-05							

Regression coefficient				ANOVA				Statistic		
B_1	7.26E-11	3.21E-01	7.53E-01							
B_2	2.24E-21	6.85E-01	5.04E-01							
Energy Production (MWh) & $DSCR_{max}$ (IDR)										
z_0	5.04E+03	3.18E-04	1.00E+00	3.08E+10	3.08E+09	3.14E+10	<0.0001	9.82E-02	1.47E+00	0.9938
A_{01}	4.46E+02	9.76E-04	9.99E-01							
B_{01}	1.10E-06	7.80E-03	9.94E-01							
B_{02}	-5.69E-18	-9.98E-04	9.99E-01							
B_{03}	3.06E-28	3.73E-03	9.97E-01							
A_1	6.60E-04	1.17E-04	1.00E+00							
A_2	-1.21E-05	-2.56E-03	9.98E-01							
A_3	-2.53E-07	-1.02E-03	9.99E-01							
B_1	1.14E-11	1.18E-03	9.99E-01							
B_2	-1.44E-22	-7.99E-04	9.99E-01							

Table 9 presents the parameters of the quadratic regression models for the analyzed response relationships. For the Debt Service Maximum–revenue relationship, the positive coefficients A_{01} = 8.92E+09, B_{02} = 5.87E-10 and A_2 = 3.44E-03 contribute to the response in the higher-value region. In contrast, B_{01} = -5.48E+01, B_{03} = 1.47E-20, A_1 = -2.96E-01, and A_3 = -1.23E-05 contribute to the surface response toward lower values. The coefficients B_1 = 7.26E-11 and B_2 = 2.24E-21 indicate relatively small interaction effects. The combined coefficients produce a color gradient from red and yellow toward green and blue. The R^2 value of 0.9978 indicates a very high degree of model fit. For the energy production–Debt Service Maximum relationship, the positive coefficients A_{01} = 4.46E+02, B_{01} = 110E-06, B_{03} = 3.06E-28, A_1 =6.60E-04, and B_1 =1.14E-11 contribute to the higher initial response region. Conversely, B_{02} = -569E-18, A_2 = -1.21E-05, A_3 = -2.53E-07, and B_2 = -1.44E-22 contribute to the response toward lower values.

Visually, the combination of these coefficients produces a transition from red toward blue as energy production and Debt Service Maximum decline. The R^2 value of 0.9938 indicates that the response pattern is also represented very well by the model. This finding is consistent with solar energy project finance studies showing that revenue, operating expenditure, CFADS, and DSCR are closely connected in assessing a project's ability to meet debt obligations (Bandaru et al., 2021).

These results demonstrate that declining asset performance not only reduces energy production and revenue but also simultaneously reduces the project's capacity to meet its debt service obligations. Therefore, construction quality, component selection, and maintenance strategies are factors that directly influence the project's life-cycle cash flow and debt service capacity. The transition in response from the red zone toward the blue zone represents a progressive reduction in the project's financial capacity throughout its operational lifetime.

5. CONCLUSION

Based on the analysis of the technical and financial performance of the solar PV project over its 25-year operational period. The main conclusions of this study are as follows:

1. Energy production declines with module degradation. Annual energy production decreases from 37,230 MWh in the first year to 33,010 MWh in the 25th year, with a strong relationship between operating year, degradation factor, and energy production (R^2 = 0.9997).
2. The project's financial performance changes throughout its operational lifetime. Revenue and CFADS decline, while OPEX increases. CFADS decreases from IDR 32.36 billion to IDR 20.49

billion between the first and 25th years, reflecting the combined effect of lower energy production and increasing OPEX.

3. The Response Surface models demonstrate strong relationships among technical and financial parameters. The CFADS–Revenue and Energy Production–CFADS models achieve R^2 values of 0.9987 and 0.9958, respectively. The Debt Service Maximum–Revenue and Energy Production–Debt Service Maximum models also show strong model fit, with R^2 values of 0.9978 and 0.9938, respectively.
4. The calculated debt service capacity declines over the project lifetime. Based on a minimum DSCR of 1.25, the Debt Service Maximum decreases from IDR 25.89 billion in the first year to IDR 16.39 billion in the 25th year. This result demonstrates that changes in energy production, revenue, and CFADS are reflected in the project's calculated capacity to support annual debt service

5.1. Practical Implication

The results highlight the importance of considering module degradation, asset quality, component selection, and maintenance from the planning stage because these factors affect long-term energy production and project cash flow. The calculated CFADS and Debt Service Maximum can also provide supporting information for financing and debt sizing decisions. The proposed analysis method can support operational planning by providing a quantitative basis for monitoring degradation, forecasting annual energy production and revenue, planning OPEX, and assessing changes in CFADS and DSCR throughout the project lifetime. By linking technical performance with financial indicators, project operators and financial decision makers can use the model to identify potential changes in cash flow and debt service capacity at an early stage and adjust maintenance, operational, and financing plans accordingly. This integrated approach is consistent with previous research showing that technical performance, operating costs, cash flow, and financing decisions are closely connected in the economic management of solar PV projects.

5.2. Limitations and Future Research

This study is based on a single 25 MW utility-scale solar PV project with an assumed module degradation rate of 0.5% per year. Future research should consider different project sizes, degradation assumptions, tariff scenarios, OPEX escalation, and financing structures to provide a broader assessment of long-term financial performance and debt service capacity.

6. REFERENCES

Abolhosseini, S., & Heshmati, A. (2014). The main support mechanisms to finance renewable energy development. *Renewable and Sustainable Energy Reviews*, *40*, 876–885. https://doi.org/10.1016/j.rser.2014.08.013

Al Garni, H. Z., & Awasthi, A. (2017). Solar PV power plant site selection using a GIS-AHP based approach with application in Saudi Arabia. *Applied Energy*, *206*(October), 1225–1240. https://doi.org/10.1016/j.apenergy.2017.10.024

Al Garni, H. Z., Awasthi, A., & Wright, D. (2019). Optimal orientation angles for maximizing energy yield for solar PV in Saudi Arabia. *Renewable Energy*, *133*, 538–550. https://doi.org/10.1016/j.renene.2018.10.048

Alberto, C., Marchioni, A., & Baschieri, D. (2022). Impact of financing and payout policy on the economic profitability of solar photovoltaic plants. *International Journal of Production Economics*, *244*, 1–19. https://doi.org/10.1016/j.ijpe.2021.108338

Alonso-Conde, A. B., & Rojo-Suárez, J. (2020). On the effect of green bonds on the profitability and credit quality of project financing. *Sustainability (Switzerland)*, *12*(16). https://doi.org/10.3390/su12166695

Andrés, A., Aguiar[1], A., David, J., Dueñas, E., Salas Jiménez, F. V., López Vásquez, S. E., & Aguiar, A. (2025). Analysis Of Weighted Average Cost Of Capital (WACC) As a Valuation Element And The Influence Of The Capm Model In Emerging Countries. *Scientific Culture*, *11*(4), 991–1003. https://doi.org/10.5281/zenodo.11042577

Ang, G., Burli, P., & Röttgers, D. (2017). The empirics of enabling investment and innovation in renewable energy. *OECD Environment Working Papers*, (123). https://doi.org/10.1787/67d221b8-en

Arhinful, R., & Radmehr, M. (2023). The effect of financial leverage on financial performance: evidence from non-financial institutions listed on the Tokyo stock market. *Journal of Capital Markets Studies*, *7*(1), 53–71. https://doi.org/10.1108/JCMS-10-2022-0038

Ari, I., & Koc, M. (2021). Towards sustainable financing models: A proof-of-concept for a waqf-based alternative financing model for renewable energy investments. *Borsa Istanbul Review*, *21*, 46–56. https://doi.org/10.1016/j.bir.2021.03.007

Ariyadi, S. B., & Purwanto, W. W. (2024). Development Strategies for Grid-Connected Utility-Scale Solar Photovoltaic to Increase Renewable Energy Penetration. *CSID Journal of Infrastructure Development*, *7*(3), 478–495. https://doi.org/10.7454/jid.v7.i3.1164

Arofah, U., Hakim, M. S., & Alfarizi, M. (2025). Capital efficiency and organizational performance: A dynamic panel analysis of Weighted Average Cost of Capital (WACC) and ROA in Indonesia's healthcare sector. *Journal of Applied Sciences in Accounting, Finance, and Tax*, *8*(1), 26–40. https://doi.org/10.31940/jasafint.v8i1.26-40

Asian Development Bank. (2019). Renewable Energy Financing Schemes for Indonesia. In *Asian Development Bank* (Number November). https://www.adb.org/sites/default/files/publication/541531/renewable-energy-financing-indonesia.pdf

Ayantokun, A. S., Ogunniyi, O. J., Matambo, T. S., Van der Merwe, I., Rashama, C., & Van Niekerk, J. A. (2026). Comparative TEA–LCA of CHP, Biomethane, and Hybrid Biogas Utilization Pathways for Poultry Manure with Fruit and Vegetable Waste Co-Digestion Systems. *Sustainability (Switzerland)*, *18*(3), 1–24. https://doi.org/10.3390/su18031483

Azhgaliyeva, D., Beirne, J., & Mishra, R. (2023). What matters for private investment in renewable energy? *Climate Policy*, *23*(1), 71–87. https://doi.org/10.1080/14693062.2022.2069664

Badri, R. M., Al kaissi, Z. A., Sutanto, M., & Alobaidi, M. k. (2022). Investigating the rheological properties of asphalt binder incorporating different crumb rubber contents based on a response surface methodology. *Journal of King Saud University - Engineering Sciences*, *34*(5), 322–328. https://doi.org/10.1016/j.jksues.2020.10.009

Bandaru, S. H., Becerra, V., Khanna, S., Espargilliere, H., Torres Sevilla, L., Radulovic, J., Hutchinson, D., & Khusainov, R. (2021). A general framework for multi-criteria based feasibility studies for solar energy projects: Application to a real-world solar farm. *Energies*, *14*(8), 1–34. https://doi.org/10.3390/en14082204

Bonazzi, G., & Iotti, M. (2014). Evaluation of biogas plants by the application of an internal rate of return and debt service coverage approach. *American Journal of Environmental Sciences*, *11*(1), 35–45. https://doi.org/10.3844/ajessp.2015.35.45

Burke, P. J., Widnyana, J., Anjum, Z., Aisbett, E., Resosudarmo, B., & Baldwin, K. G. H. (2019). Overcoming barriers to solar and wind energy adoption in two Asian giants: India and Indonesia. *Energy Policy*, *132*(April), 1216–1228. https://doi.org/10.1016/j.enpol.2019.05.055

Campisi, D., Gitto, S., & Morea, D. (2018). Shari'ah-compliant finance: A possible novel paradigm for green economy investments in Italy. *Sustainability (Switzerland)*, *10*(11), 1–12. https://doi.org/10.3390/su10113915

Chacko, J. P., & Padmakumari, L. (2024). Does investor base affect the firm-level ex-ante cost of equity capital? *IIMB Management Review*, *36*(2), 146–156. https://doi.org/10.1016/j.iimb.2024.04.003

Cifuentes, R., Gómez, T., & Jara, A. (2025). Capital ratios and the Weighted Average Cost of

Capital: Evidence from Chilean banks. *Latin American Journal of Central Banking*, *6*(1), 1–17. https://doi.org/10.1016/j.latcb.2024.100143

Clews, R. J. (2016). Project Finance for the International Petroleum Industry. In S. Ikeda (Ed.), *Project Finance for the International Petroleum Industry*. Nikki Levy. https://doi.org/10.1016/B978-0-12-800158-5.00024-4

Costa Climent, R., & Haftor, D. M. (2021). Value creation through the evolution of business model themes. *Journal of Business Research*, *122*, 353–361. https://doi.org/10.1016/j.jbusres.2020.09.007

Diyono, D., Cappon, H., Kujawa-Roeleveld, K., & Keesman, K. J. (2023). Designing Sustainable Domestic Electricity Supply from Renewable Energy Mixes: Application to Java and Bali, Indonesia. *Energies*, *16*(22), 1–19. https://doi.org/10.3390/en16227461

Dong, C. G. (2012). Feed-in tariff vs. renewable portfolio standard: An empirical test of their relative effectiveness in promoting wind capacity development. *Energy Policy*, *42*, 476–485. https://doi.org/10.1016/j.enpol.2011.12.014

Erdiwansyah, E., Mahidin, M., Husin, H., Nasaruddin, N., Khairil, K., Zaki, M., & Jalaluddin, J. (2021). Investigation of availability, demand, targets, and development of renewable energy in 2017–2050: a case study in Indonesia. *International Journal of Coal Science and Technology*, *8*(4), 483–499. https://doi.org/10.1007/s40789-020-00391-4

Falih, H., Hamed, A. J., & Khalifa, A. H. N. (2022). Techno-economic assessment of a hybrid connected PV solar system. *International Journal of Air-Conditioning and Refrigeration*, *30*(1). https://doi.org/10.1007/s44189-022-00003-7

Firouzi, A., & Meshkani, A. (2021). Risk-based optimization of the debt service schedule in renewable energy project finance. *Utilities Policy*, *70*, 1–12. https://doi.org/10.1016/j.jup.2021.101197

Frank, M. Z., & Shen, T. (2016). Investment and the weighted average cost of capital. *Journal of Financial Economics*, *119*(2), 300–315. https://doi.org/10.1016/j.jfineco.2015.09.001

Gatti, S. (2013). Valuing the Project and Project Cash Flow Analysis. In *Project Finance in Theory and Practice*. https://doi.org/10.1016/b978-0-12-391946-5.00005-0

Guest, P. M., Wang, M., & Welte, S. (2026). The effect of the cost of capital on private equity buyout performance. *Journal of Corporate Finance*, *100*, 1–20. https://doi.org/10.1016/j.jcorpfin.2026.103005

Halimatussadiah, A., Kruger, W., Wagner, F., Afifi, F. A. R., Lufti, R. E. G., & Kitzing, L. (2024). The country of perpetual potential: Why is it so difficult to procure renewable energy in Indonesia? *Renewable and Sustainable Energy Reviews*, *201*, 1–11. https://doi.org/10.1016/j.rser.2024.114627

Hasudungan, H. W. V., & Sabaruddin, S. S. (2018). Financing Renewable Energy in Indonesia: A CGE Analysis of Feed-In Tariff Schemes. *Bulletin of Indonesian Economic Studies*, *54*(2), 233–264. https://doi.org/10.1080/00074918.2018.1450961

Huaman-Roque, A. J., Cuyate-Reque, P., Cueva-Ruesta, J., & Cordova-Buiza, F. (2025). Impact of Weighted Average Cost of Capital and Profitability on Economic Value Added of Firms in the Industrial Sector. *Journal of Risk and Financial Management*, *18*(11), 1–16. https://doi.org/10.3390/jrfm18110650

Imasiku, K. (2021). Research Article A Solar Photovoltaic Performance and Financial Modeling Solution for Grid-Connected Homes in Zambia. *International Journal of Photoenergy*, *2021*, 1–13. https://doi.org/10.1155/2021/8870109

IRENA. (2020). Indonesia Energy Transition Outlook. In *Essential Concepts of Global Environmental Governance*. International Renewable Energy Agency. https://doi.org/10.7551/mitpress/9780262037419.003.0003

Jadidi, H., Firouzi, A., Rastegar, M. A., & Zandi, M. (2020). Bayesian updating of solar resource data for risk mitigation in project finance. *Solar Energy*, *207*(August), 1390–1403. https://doi.org/10.1016/j.solener.2020.07.096

Kalkavan, H., & Eti, S. (2021). Determining Optimal Islamic Financing Methods for Small-Scale

Sustainable Energy Investments Regarding Socio-Economic Welfare. *Contributions to Management Science*, 271–283. https://doi.org/10.1007/978-3-030-76783-9_20

Karim, R. (2023). Prospects and challenges of Islamic finance instruments for low-carbon energy transitions: a legal analysis from an energy justice perspective. *Journal of Energy and Natural Resources Law*, *41*(2), 195–209. https://doi.org/10.1080/02646811.2023.2187550

Kasri, R. A., Rulindo, R., Sakti, M. R. P., Rifqi, M., & Yuniar, A. (2024). Islamic Financing for Renewable Energy in Indonesia: Unlocking Potential Demand From Gcc Investors. *Journal of Islamic Monetary Economics and Finance*, *10*(2), 301–328. https://doi.org/10.21098/jimf.v10i2.1846

Kayser, D. (2016). Solar photovoltaic projects in China : High investment risks and the need for institutional response. *Applied Energy*, *174*, 144–152. https://doi.org/10.1016/j.apenergy.2016.04.089

Kurihara, S., Uto, R., & Aoki, Y. (2009). A survey of the finances of new energy projects and its analysis by the cash-flow model. In *Nihon Enerugi Gakkaishi/Journal of the Japan Institute of Energy* (Vol. 88, Number 4, pp. 310–325). https://doi.org/10.3775/jie.88.310

Lam, P. T. I., & Law, A. O. K. (2018). Financing for renewable energy projects: A decision guide by developmental stages with case studies. *Renewable and Sustainable Energy Reviews*, *90*, 937–944. https://doi.org/10.1016/j.rser.2018.03.083

Langer, J., Kwee, Z., Zhou, Y., Isabella, O., Ashqar, Z., Quist, J., Praktiknjo, A., & Blok, K. (2023). Geospatial analysis of Indonesia's bankable utility-scale solar PV potential using elements of project finance. *Energy*, *283*, 1–16. https://doi.org/10.1016/j.energy.2023.128555

Limmanee, A., Udomdachanut, N., & Songtrai, S. (2016). Field performance and degradation rates of different types of photovoltaic modules : A case study in Thailand. *Renewable Energy*, *89*, 12–17. https://doi.org/10.1016/j.renene.2015.11.088

Manojkumar, N., Muthukumaran, C., & Sharmila, G. (2022). A comprehensive review on the application of response surface methodology for optimization of biodiesel production using different oil sources. *Journal of King Saud University - Engineering Sciences*, *34*(3), 198–208. https://doi.org/10.1016/j.jksues.2020.09.012

Morea, D., & Poggi, L. A. (2017). An innovative model for the sustainability of investments in the wind energy sector: The use of green sukuk in an Italian case study. *International Journal of Energy Economics and Policy*, *7*(2), 53–60.

Naumenkova, S., Tishchenko, I., Mishchenko, S., Mishchenko, V., & Ivanov, V. (2020). Assessment and mitigation of credit risks in project financing. *Banks and Bank Systems*, *15*(1), 72–84. https://doi.org/10.21511/bbs.15(1).2020.08

Okoye, C. O., & Oranekwu-Okoye, B. C. (2018). Economic feasibility of solar PV system for rural electrification in Sub-Sahara Africa. *Renewable and Sustainable Energy Reviews*, *82*, 2537–2547. https://doi.org/10.1016/j.rser.2017.09.054

Pacudan, R. (2016). Implications of applying solar industry best practice resource estimation on project financing. *Energy Policy*, *95*, 489–497. https://doi.org/10.1016/j.enpol.2016.02.021

Paradongan, H. T., Hakam, D. F., Wiryono, S. K., Prahastono, I., Aditya, I. A., Banjarnahor, K. M., Sinisuka, N. I., & Asekomeh, A. (2024). Techno-economic feasibility study of solar photovoltaic power plant using RETScreen to achieve Indonesia energy transition. *Heliyon*, *10*(7), 1–22. https://doi.org/10.1016/j.heliyon.2024.e27680

Pascual, J., Marroyo, L., Martinez-moreno, F., García, M., Marcos, J., & Lorenzo, E. (2021). Long-term degradation rate of crystalline silicon PV modules at commercial PV plants : An 82-MWp assessment over 10 years. *Progress in Photovoltaics: Research and Applications*, *29*(12), 1294–1302. https://doi.org/10.1002/pip.3456

Piergallini, A. (2026). Corporate tax cuts, the cost of capital, and economic activity. *Quarterly Review of Economics and Finance*, *108*, 1–8. https://doi.org/10.1016/j.qref.2026.102162

Rodríguez, R. A. (2024). A Required Debt Service Coverage Ratio Related to the Economic Value of the Asset Involved. *Journal of Financial Risk Management*, *13*(04), 618–642. https://doi.org/10.4236/jfrm.2024.134029

Satpute, J., Ghongade, G., Petrů, J., Campli, S., Yadav, S., Sonawane, P. K., Venu, H., Bashir, M. N., Soudagar, M. E. M., & Channapattana, S. (2025). Computational study on water based hybrid photovoltaic systems with different absorber configurations. *Scientific Reports*, *15*(1), 1–16. https://doi.org/10.1038/s41598-024-82690-3

Setyorini, D., Qodim, A., Sabdha, S., Yudha, P., Prasetya, F., Yuktii, A., Ramadhani, N., Zaimul, S., & Khotimah, S. K. (2026). The evaluation of RSM optimization and kinetics modeling of essential oil extraction from Citrus hystrix leaves using microwave - assisted hydrodistillation. *Journal of King Saud University – Engineering Sciences*, *38*(26), 1–22. https://doi.org/10.1007/s44444-025-00091-x

Siswantoro, & Mahmud, A. (2023). The impact of Islamic financial development on renewable energy production in Islamic countries. *Asian Journal of Islamic Management (AJIM)*, *5*(1), 54–68. https://doi.org/10.20885/AJIM. vol5.iss1.art4

Sopian, K., Ali, B., & Asim, N. (2011). Strategies for renewable energy applications in the organization of Islamic conference (OIC) countries. *Renewable and Sustainable Energy Reviews*, *15*(9), 4706–4725. https://doi.org/10.1016/j.rser.2011.07.081

Steffen, B. (2018). The importance of project finance for renewable energy projects. *Energy Economics*, *69*, 280–294. https://doi.org/10.1016/j.eneco.2017.11.006

Sunarso, A., Ibrahim-Bathis, K., Murti, S. A., Budiarto, I., & Ruiz, H. S. (2020). GIS-based assessment of the technical and economic feasibility of utility-scale solar PV plants: Case study in West Kalimantan province. *Sustainability (Switzerland)*, *12*(15), 1–12. https://doi.org/10.3390/MATH8081350

Sung, S., & Jung, W. (2019). Economic competitiveness evaluation of the energy sources: Comparison between a financial model and levelized cost of electricity analysis. *Energies*, *12*(21), 1–21. https://doi.org/10.3390/en12214101

Ulfah, I. F., & Al-Kahfi, M. F. (2026). Development of Green Sukuk in Indonesia Based on The Pillars of Sustainable Development. *Perisai : Islamic Banking and Finance Journal*, *10*(1), 78–98. https://doi.org/10.21070/perisai.v10i1.2040

Valaskova, K., Durana, P., Kliestik, T., & Vojtekova, S. (2023). Level of pandemic consequences for the indebtedness of the Slovak hospitality sector. *Investment Management and Financial Innovations*, *20*(4), 334–349. https://doi.org/10.21511/imfi.20(4).2023.27

Wall, R., Grafakos, S., Gianoli, A., & Stavropoulos, S. (2019). Which policy instruments attract foreign direct investments in renewable energy? *Climate Policy*, *19*(1), 59–72. https://doi.org/10.1080/14693062.2018.1467826

Wildgruber, K., Thompson, C., & Egli, F. (2026). An empirically validated open-access approach for calculating the cost of capital of renewables. *Energy Strategy Reviews*, *64*, 1–14. https://doi.org/10.1016/j.esr.2026.102103

Wong, R., & Dewayanti, A. (2024). Indonesia's energy transition: Dependency, subsidies and renewables. *Asia and the Pacific Policy Studies*, *11*(2), 1–22. https://doi.org/10.1002/app5.391

Yescombe, E. R. (2007). *Public-Private Partnerships*. Elsevier Ltd. https://doi.org/https://doi.org/10.1016/B978-0-7506-8054-7.X5022-9

Yuliah, Y., Triana, L., Khadijah, I., & Afriani, R. I. (2023). Capital Cost Analysis Using the Weighted Average Cost of Capital (Wacc) Method At Pt. Kalbe Farma Tbk. *International Journal of Multidisciplinary Research and Literature*, *2*(3), 342–346. https://doi.org/10.53067/ijomral.v2i3.122