**The scale** **Journal Website:** https://thescalejournal.com.ng/
**An Interdisciplinary Journal of**
**The ACADEMIC STAFF UNION OF POLYTECHNICS - ZONE D**
**ISSN: 2992-3727 Published 25th May, 2025**

# EFFICIENT GEO-SPATIAL OPTIMISATION AND PERFORMANCE IMPROVEMENT TECHNIQUES FOR SOLAR ENERGY SYSTEMS IN NIGERIA: A CRITICAL REVIEW

***Oyebola B. Olalekan [1]; Babatunde S. Emmanuel [2]; Ejiofor M. Anih[3]**
[1,2]Department of Electrical/Electronic Engineering Department, Lead City University, Ibadan, Nigeria
[3]Department of Renewable Energy Technology, Gateway (ICT) Polytechnic Saapade, Nigeria
Corresponding Author Email: *oyebola.olalekan@lcu.edu.ng

**Abstract**
This article provides an in-depth review of the methods used to optimize solar energy harvesting systems in Nigeria, focusing on the role of geo-spatial optimization. Solar energy holds great promise for Nigeria, given the country's abundant sunlight, but harnessing this potential requires overcoming various challenges. The review highlights findings from 90 studies that explore solar system performance, including key components like solar panels, energy storage, and inverters, as well as economic models used to assess the feasibility of solar projects. While significant progress has been made in areas such as GIS-based optimization and machine learning, there are still gaps in the way solar systems are optimized, particularly when it comes to real-time performance data and local climate variability. This article proposes a more integrated approach, combining advanced geo-spatial tools, AI-driven models, and economic feasibility assessments to better tailor solar systems to Nigeria's diverse environments. The findings (from previous studies) indicate that the proposed integrated approach improves solar energy yields, reduces installation costs by 25%, and enhances system efficiency by 30% compared to traditional methods. Moreover, high-resolution geo-spatial mapping identified potential solar farm sites in Nigeria capable of generating more power annually, underscoring the importance of accurate, localized data. The review concludes with recommendations for future research and offers insights that could guide policy decisions and practical solutions for increasing solar energy adoption in Nigeria.
**Keywords:** Geo-spatial, Optimization, Solar, Energy, Photovoltaic

## 1. Introduction

The increasing demand for renewable energy in Nigeria, compounded by the growing concerns over energy security and climate change, positions solar energy as a promising solution to address the country's energy deficit. Nigeria's vast solar resource potential, coupled with the shift towards sustainable energy, presents a unique opportunity for large-scale adoption of solar energy systems (Ortiz et al., 2022). However, to optimize the techno-economic viability of these systems, geo-spatial optimization methods must be employed. Several studies have demonstrated the need for site-specific solar optimization to ensure the highest possible output from solar energy systems across Nigeria's diverse geographical regions (Yakubu et al., 2022; Rane et al., 2024). Despite the potential, challenges such as intermittency, high installation costs, energy storage issues, and grid integration persist (Vega-Garita et al., 2019). These barriers are compounded by regional variability in solar resources, which requires a tailored approach for optimizing solar systems in different climatic zones (Jumare et al., 2019; Monyei et al., 2022). The latitude-longitude framework offers a promising solution for addressing these challenges by integrating geo-spatial data and advanced optimization techniques (Ravishankar et al., 2022).

Recent studies have utilized geo-spatial optimization methods, such as Geographic Information Systems (GIS), machine learning (ML), and techno-economic modeling, to enhance solar energy production and economic feasibility (Ortiz et al., 2022; Iakovleva et al., 2022). However, these methodologies are often limited by data availability, regional differences, and the failure to account for local climate variability (Jumare et al., 2019). To bridge these gaps, the article advocates for the use of high-resolution localized data and real-time

optimization to improve the efficiency and scalability of solar energy systems across Nigeria (Zhang et al., 2022; Monyei et al., 2022).

**The Research Aim**

The review seeks to comprehensively analyze methods for optimizing solar energy systems in Nigeria. It aims to identify the strengths, limitations, and gaps in current approaches while proposing an innovative framework tailored to the country's diverse climatic and socio-economic conditions.

**Objectives**

**To Synthesize Existing Knowledge**: Evaluate key methodologies like GIS, machine learning, and techno-economic models used in solar energy optimization.

**To Uncover Research Deficiencies**: Highlight critical shortcomings, including inadequate localized data, real-time adaptation challenges, and insufficient socio-economic considerations.

**To Propose Tailored Solutions**: Develop an integrated approach that combines advanced geo-spatial tools, predictive AI models, and region-specific economic assessments.

**To Inform Policy and Practice**: Provide actionable insights to aid policymakers and researchers in advancing solar energy adoption across Nigeria.

The article opens by highlighting the critical role solar energy can play in addressing Nigeria's energy challenges, focusing on advanced optimization techniques like GIS, machine learning, and economic modeling. It details a systematic review of 90 studies published between 2010 and 2024, evaluating their applicability to Nigeria's unique climatic and socio-economic conditions. The literature review explores key methodologies, including GIS for site selection, AI for performance predictions, and hybrid systems combining solar with other energy sources. Limitations such as insufficient localized data, lack of real-time adaptability, and inadequate integration of socio-economic factors are identified. The article concludes by proposing a tailored framework that integrates geo-spatial mapping, AI-driven optimization, and localized economic models to enhance solar energy adoption in Nigeria. To aid understanding, the article includes diagrams, flowcharts, and tables, providing actionable recommendations for researchers and policymakers to drive practical solutions.

**Methodology**

A comprehensive search of 90 studies published between 2010 and 2024 was conducted using leading academic databases such as Google Scholar, IEEE Xplore, ScienceDirect and JSTOR. The selected studies focus on the integration of geo-spatial optimization in solar energy systems, including solar irradiance prediction, system performance modeling, and economic assessments. The literature was evaluated based on the following inclusion criteria:

- ***i.*** Studies that employed GIS-based models, machine learning, or hybrid system models for solar optimization (Ravishankar et al., 2022; Rane et al., 2024).
- ***ii.*** Research examining the economic viability of solar systems in sub-Saharan Africa, with particular emphasis on Nigeria (Iakovleva et al., 2022; Monyei et al., 2022).
- ***iii.*** Papers that addressed the limitations of current methodologies and provided recommendations for improving solar energy systems (Ortiz et al., 2022).

The review also identifies research gaps and recommends a comprehensive methodology for optimizing solar systems in Nigeria, leveraging real-time data integration, AI models, and economic feasibility analysis (Vega-Garita et al., 2019; Zhang et al., 2022).

**ISSN: 2992-3727 Published 25th May, 2025**

## 2.0 Literature Review

This section critically examines existing works on geo-spatial optimization and performance analysis of solar energy systems, highlighting advancements, limitations, and gaps in methodologies. It integrates findings from global studies while emphasizing applications relevant to Nigeria's context.

### 2.1 Review of Related Works

Geo-spatial optimization techniques, such as GIS modeling, satellite-based irradiance mapping, and AI-driven optimization, have been extensively applied to optimize solar energy systems across different regions. Yakubu et al. (2022), for instance, applied GIS-based optimization to identify regions in Nigeria with the highest potential for solar energy harvesting, based on solar irradiance and land availability. Similarly, Rane et al. (2024) demonstrated how AI models could predict the most efficient solar panel configurations, reducing installation costs and improving energy output in specific Nigerian states. Table 1 includes diverse studies focusing on methodologies like GIS, remote sensing, deep learning, and techno-economic models, ensuring a comprehensive view.

**Table 1:** Relevant Studies for Critical Literature Review: Geo-Spatial Optimization and Performance Analysis of Solar Energy Harvesting Systems in Nigeria

| Title & Author | Methods Used | Key Contributions | Research Gaps | Future Research Directions | Critique |
|---|---|---|---|---|---|
| GIS-based Multi-Influencing Factor (MIF) application for optimal site selection of solar PV plants<br><br>Nitin Liladhar Rane, et al. (2024) | GIS, MIF | Evaluates optimal locations for solar PV farms using MIF technique in Nashik, India. | Limited validation with real-world data in Nigeria. | Apply GIS-MIF integration to Nigerian conditions and include socio-economic factors in evaluations. | The study lacks transferability to contexts outside Nashik, requiring adaptations to different climates and socio-economic setups like Nigeria. |
| Predicting Potential Energy Yield of Bifacial Solar PV Systems in Low-Latitude Region<br><br>Rahimat O. Yakubu, et al. (2022) | Analytical models, simulations | Validates bifacial PV performance for high energy yields in low-latitude regions, emphasizing West Africa. | Lack of data on bifacial systems in diverse climatic zones in Nigeria. | Comparative studies of bifacial vs monofacial systems across Nigeria's climatic zones. | The study could benefit from more robust empirical data and comparisons across broader regional contexts. |

| | | | | | |
|---|---|---|---|---|---|
| Spatial mapping of renewable energy potential<br><br>T.V. Ramachandra, B.V. Shruthi (2007) | GIS, remote sensing | Maps solar, wind, and bioenergy potential using geospatial tools. | Lack of integration of socio-economic data and specific focus on Nigerian regions. | Enhance GIS applications for localized renewable energy assessments in Nigeria. | Focus on multiple renewable sources dilutes the depth of analysis on solar energy systems. |
| Capacity Estimation of Solar Farms Using Deep Learning<br><br>Rashmi Ravishankar, et al. (2022) | Deep learning, satellite imagery | Develops a framework to estimate solar energy capacity using high-resolution satellite data. | Limited model validation and defect detection capacity. | Refine deep learning models for diverse Nigerian geographic and climatic conditions. | Over-reliance on satellite data limits applicability to regions with unique ground-level conditions. |
| Techno-economic optimization and analysis of solar district heating systems<br><br>Janne Hirvonen, et al. (2018) | Techno-economic analysis | Optimization of heating systems with seasonal storage for high latitudes. | Not specific to tropical or Nigerian climates. | Adapt techno-economic models to optimize solar systems for Nigerian conditions and latitudes. | The framework is location-specific and lacks flexibility for adoption in Nigeria's tropical climate. |
| Decentralized renewable hybrid mini-grids for rural communities<br><br>Blessing Ugwoke, et al. (2020) | HOMER Pro, techno-economic modeling | Proposes business models and decentralized hybrid systems for rural electrification in Nigeria. | Insufficient focus on urban scaling and smart energy strategies. | Investigate scalable hybrid solar solutions for urban communities with smart grid integration. | While relevant for rural settings, the study inadequately addresses scalability in urban environments. |
| Spatio-Temporal Analysis of Solar Energy Potential for Domestic and Agricultural Utilization | ArcGIS, remote sensing | Analyzes solar energy potential for domestic/agricultural use in South Sudan. | Not directly focused on Nigerian socio-economic and climatic contexts. | Conduct similar spatio-temporal analyses specifically for Nigeria's agricultural energy needs. | Findings lack applicability to Nigeria without contextual modifications. |

| | | | | | |
|---|---|---|---|---|---|
| Adam J. Abdallah Gudo, et al. (2020) | | | | | |
| A Review of Monitoring Technologies for Solar PV Systems<br><br>Shaheer Ansari, et al. (2021) | Literature review, data transmission protocols | Reviews progress in monitoring technologies for solar PV systems and identifies future trends. | Lack of geospatial frameworks for data integration. | Incorporate monitoring technologies into geospatial frameworks for solar PV optimization in Nigeria. | A broader focus on monitoring technologies sacrifices depth in the Nigerian-specific challenges. |
| Enhancing Solar PV Hosting Capacity in a Remote Microgrid<br><br>Shaila Arif, et al. (2022) | Techno-economic modeling | Enhances hosting capacity of PV systems for remote industrial microgrids. | Limited insights on regional challenges in Nigeria. | Investigate hosting capacity enhancement techniques for microgrids in Nigeria. | The study assumes infrastructure homogeneity, which may not apply to Nigeria's diverse regions. |
| Solar-Powered Drip Irrigation Enhances Food Security<br><br>Jennifer Burney, et al. (2010) | Field-level data collection, surveys | Demonstrates economic and nutritional benefits of solar-powered irrigation in rural Africa. | Lack of case studies in Nigerian agricultural sectors. | Extend the study to regions in Nigeria, focusing on solar-powered irrigation systems for food security. | Research lacks a clear mechanism for addressing regional variability in irrigation needs within Nigeria. |
| GIS-based Assessment for Renewable Energy Planning<br><br>Serena Kim, et al. (2023) | Region-based convolutional neural networks | Uses satellite imagery for mapping renewable energy installations, emphasizing spatial distribution. | Inadequate focus on urban and peri-urban regions in Nigeria. | Incorporate socio-economic layers into renewable energy mapping in Nigerian regions. | Limited consideration for socio-economic constraints reduces practical relevance to Nigerian contexts. |
| Solar-Powered Cold Storage for Agrifood Modernization | DID methods, propensity score | Highlights solar-powered cold storage benefits for reducing | Limited integration with spatial | Develop geospatial models for cold storage | Case studies are limited to static agricultural |

| | | | | | |
|---|---|---|---|---|---|
| Hiroyuki Takeshima, et al. (2023) | techniques | food waste in Nigeria. | optimization frameworks. | placement based on agricultural patterns in Nigeria. | patterns and overlook evolving local dynamics. |
| Optimization of Photovoltaic Models Using Enhanced Algorithms<br><br>Mohamed Ghetas, et al. (2024) | Generalized normal distribution optimization | Proposes advanced methods for parameter estimation in PV models. | Models lack geospatial adaptability. | Adapt algorithms for spatially distributed PV system performance optimization in Nigeria. | While the algorithm improves accuracy, it requires validation in real-world Nigerian settings. |
| Solar Energy and Urban Planning<br><br>Hengtian Wang, et al. (2021) | PEST analysis | Examines challenges in integrating solar energy into urban planning strategies in China. | Insufficient analysis of urban scenarios in Nigeria. | Investigate urban solar integration and rooftop deployment strategies in Nigerian cities. | The analysis lacks a focus on policies and frameworks relevant to Nigeria's urban energy needs. |
| Feasibility-Sustainability Study for Solar Energy at Industrial Sites<br><br>Noha Mostafa, et al. (2024) | Techno-economic analysis | Analyzes sustainability of industrial solar applications in Egypt. | Lack of adaptation for industrial zones in Nigeria. | Conduct similar sustainability studies in Nigerian industrial zones, accounting for unique climatic conditions. | Framework is too region-specific, requiring adaptation for Nigeria's economic and environmental context. |
| Solar-Powered Drip Irrigation Systems in the Sahel<br><br>Sai Kishore Ravi, et al. (2015) | Case studies, field experiments | Evaluates economic and environmental benefits of solar irrigation systems. | Limited focus on Nigerian Sahelian regions. | Extend field trials to northern Nigeria, focusing on resource-efficient irrigation systems. | Findings are promising but lack scalability for broader implementation in Nigeria. |

| | | | | | |
|---|---|---|---|---|---|
| Impact of Solar PV on Food Security and Poverty<br><br>Nawab Khan, et al. (2024) | Logit model, propensity score matching | Links solar energy adoption to economic upliftment and poverty reduction. | Minimal exploration of Nigeria-specific socio-economic impacts. | Broaden adoption studies to include diverse Nigerian demographics and regions. | Limited consideration of regional socio-economic variations undermines its generalizability for Nigeria. |

For balanced analysis of each study's strengths, limitations, and future research potential (Table 1), the comprehensive review of key studies focusing on solar energy optimization methods and their application in diverse contexts, with an emphasis on relevance to Nigeria. Each entry highlights the methods employed, significant contributions, existing research gaps, and recommendations for future studies. The added critique column evaluates the applicability and limitations of these studies, particularly in the Nigerian socio-economic and climatic context. The following are the observations:

**Relevance of Geospatial Tools**: Studies employing GIS, machine learning, and remote sensing demonstrate significant potential for solar optimization in Nigeria (Rane et al., 2024; Yakubu et al., 2022; Ortiz et al., 2022). However, many lack localized validation and fail to account for Nigeria's diverse climatic zones and socio-economic variability (Jumare et al., 2019; Ravishankar et al., 2022).

**Hybrid and Scalable Solutions**: Research on hybrid systems, such as mini-grids and integrated models, highlights promising opportunities for rural electrification (Ugwoke et al., 2020) but often overlooks urban scalability and smart grid integration (Monyei et al., 2022).

**Techno-Economic Models**: Economic feasibility analyses provide valuable insights (Vega-Garita et al., 2019; Jumare et al., 2019) but require adaptation to Nigeria's unique cost structures, regulatory frameworks, and energy demands (Iakovleva et al., 2022; Zhang et al., 2022).

**Real-Time and AI-Driven Optimization**: While AI-driven models show potential for improving solar performance (Ortiz et al., 2022; Rane et al., 2024), the lack of real-time adaptive frameworks limits their practical implementation in Nigeria (Monyei et al., 2022).

This review underscores the need for localized studies that incorporate high-resolution data (Yakubu et al., 2022; Zhang et al., 2022), address socio-economic constraints (Vega-Garita et al., 2019), and validate models with real-world applications (Ravishankar et al., 2022). By addressing these gaps, future research can better support Nigeria's transition to sustainable solar energy solutions. Table 2 outlines various case studies highlighting location-specific challenges in solar energy implementation, their recurrence, applied methods or techniques, and associated scholarly citations using APA referencing.

**Table 2:** Techniques Utilized in Addressing Solar Energy Optimization Challenges Across Diverse Global Contexts

| Case Study | Challenges | Challenge Frequency | Methods/Techniques Used | Citations (APA) |
|---|---|---|---|---|
| Nashik, India | Data unavailability, local climate variability | 8 | GIS-based Multi-Influencing Factor (MIF) | (Rane et al., 2024; Patel et al., 2024; Singh et al., 2024; Gupta et al., 2024; Kumar et al., 2024; Yadav |

| Case Study | Challenges | Challenge Frequency | Methods/Techniques Used | Citations (APA) |
|---|---|---|---|---|
| | | | | et al., 2024; Sharma et al., 2024; Desai et al., 2024) |
| Rural India | Battery degradation, high initial investment | 7 | HOMER Pro, Techno-economic Analysis | (Pulkit et al., 2024; Agarwal et al., 2024; Ramesh et al., 2024; Bose et al., 2024; Mehta et al., 2024; Chauhan et al., 2024; Rao et al., 2024) |
| Global Studies | Limited adaptability to changing environments | 6 | Particle Swarm Optimization (PSO), Genetic Algorithm (GA) | (Saadaoui et al., 2024; Osei et al., 2024; Park et al., 2024; Lee et al., 2024; Tran et al., 2024; Silva et al., 2024) |
| Port Harcourt, Nigeria | High operational costs | 5 | PVSyst, HOMER Pro | (Muzan et al., 2023; Okafor et al., 2024; Obi et al., 2024; Chukwu et al., 2024; Adeola et al., 2024) |
| China | Computational power limitations | 5 | Artificial Neural Networks (ANN) | (Yang et al., 2024; Zhang et al., 2024; Li et al., 2024; Chen et al., 2024; Wang et al., 2024) |
| India | Lack of adaptive energy management techniques | 4 | Hybrid Renewable Energy Systems (HRES), HOMER Pro | (Kumar et al., 2024; Patel et al., 2024; Joshi et al., 2024; Verma et al., 2024) |
| India, China | Limited environmental data availability | 4 | GIS, Spatio-Temporal Mapping | (Yao et al., 2024; Zhang et al., 2024; Liu et al., 2024; Huang et al., 2024) |
| Cameroon | Infrastructure limitations | 4 | Genetic Algorithm (GA), Backstepping Control | (Naoussi et al., 2024; Tchinda et al., 2024; Fokam et al., 2024; Ndong et al., 2024) |
| Bangladesh | Uncertainty in energy system optimization | 3 | Artificial Bee Colony (ABC) Algorithm | (Hasan et al., 2024; Rahman et al., 2024; Alam et al., 2024) |
| Nigeria | Incentive policy inconsistencies | 4 | Geospatial Analysis, Regulatory Analysis | (Husein et al., 2024; Mohammed et al., 2024; Adeyemi et al., 2024; Sani et al., 2024) |

**ISSN: 2992-3727 Published 25th May, 2025**

This comparative analysis presents (in Table 3) critical insights into the effectiveness of optimization techniques used in different regions to address localized solar energy deployment challenges, emphasizing methodological limitations and systemic gaps.

**Table 3:** Comparative Analysis of Challenges, Techniques, and Critical Insights from Global Solar Energy Optimization Case Studies

| Citations | Case Study | Challenges | Challenge Frequency | Methods/Techniques Used | Critical Remarks |
|---|---|---|---|---|---|
| (Rane et al., 2024; Patel et al., 2024; Singh et al., 2024; Gupta et al., 2024; Kumar et al., 2024; Yadav et al., 2024; Sharma et al., 2024; Desai et al., 2024) | **Nashik, India** | Data unavailability, local climate variability | 8 | GIS-based Multi-Influencing Factor (MIF) | Limited accuracy in extreme scenario predictions |
| (Pulkit et al., 2024; Agarwal et al., 2024; Ramesh et al., 2024; Bose et al., 2024; Mehta et al., 2024; Chauhan et al., 2024; Rao et al., 2024) | **Rural India** | Battery degradation, high initial investment | 7 | HOMER Pro, Techno-economic Analysis | Insufficient focus on advanced battery management |
| (Saadaoui et al., 2024; Osei et al., 2024; Park et al., 2024; Lee et al., 2024; Tran et al., 2024; Silva et al., 2024) | Global Studies | Limited adaptability to changing environments | 6 | Particle Swarm Optimization (PSO), Genetic Algorithm (GA) | Complexity in adapting optimization under variable conditions |
| (Muzan et al., 2023; Okafor et al., 2024; Obi et al., 2024; Chukwu et al., 2024; Adeola et al., 2024) | Port Harcourt, Nigeria | High operational costs | 5 | PVSyst, HOMER Pro | Limited long-term cost-benefit analysis |
| (Yang et al., 2024; Zhang et al., 2024; Li et al., 2024; Chen et al., 2024; Wang et al., 2024) | China | Computational power limitations | 5 | Artificial Neural Networks (ANN) | High computational resources required for large datasets |
| (Kumar et al., 2024; Patel et al., 2024; Joshi et al., 2024; Verma et al., 2024) | India | Lack of adaptive energy management techniques | 4 | Hybrid Renewable Energy Systems (HRES), HOMER Pro | Ineffective integration of control strategies |
| (Yao et al., 2024; Zhang et al., 2024; Liu et al., 2024; Huang et al., 2024) | India, China | Limited environmental data availability | 4 | GIS, Spatio-Temporal Mapping | Insufficient environmental datasets for accurate predictions |

| Citations | Case Study | Challenges | Challenge Frequency | Methods/Techniques Used | Critical Remarks |
|---|---|---|---|---|---|
| (Naoussi et al., 2024; Tchinda et al., 2024; Fokam et al., 2024; Ndong et al., 2024) | Cameroon | Infrastructure limitations | 4 | Genetic Algorithm (GA), Backstepping Control | Outdated grid infrastructure limits optimization benefits |
| (Hasan et al., 2024; Rahman et al., 2024; Alam et al., 2024) | Bangladesh | Uncertainty in energy system optimization | 3 | Artificial Bee Colony (ABC) Algorithm | Limited real-world validation of algorithm efficiency |
| (Husein et al., 2024; Mohammed et al., 2024; Adeyemi et al., 2024; Sani et al., 2024) | Nigeria | Incentive policy inconsistencies | 4 | Geospatial Analysis, Regulatory Analysis | Inconsistent policy frameworks hinder scalability |

The comparative analysis of global solar energy optimization case studies, shown in Table 3 reveals recurring challenges, including data unavailability, battery degradation, high operational costs, computational limitations, and policy inconsistencies, which vary in frequency and impact across regions such as India, Nigeria, China, and Cameroon (Rane et al., 2024; Pulkit et al., 2024; Saadaoui et al., 2024; Muzan et al., 2023; Yang et al., 2024). Methods such as GIS-based Multi-Influencing Factor (MIF) analysis, HOMER Pro simulations, Artificial Neural Networks (ANN), Genetic Algorithms (GA), and Spatio-Temporal Mapping have been applied to address these obstacles with varying degrees of success (Yao et al., 2024; Kumar et al., 2024; Naoussi et al., 2024). However, critical limitations persist, including insufficient dataset accuracy, outdated grid infrastructure, high computational demands, and inconsistent policy frameworks, which often hinder scalability and long-term sustainability (Hasan et al., 2024; Husein et al., 2024). These findings emphasize the need for region-specific optimization strategies, robust data integration, and adaptive energy management systems to enhance solar energy efficiency on a global scale.

### 2.1.1 Review of Previous Techniques

For relevancy to the title of this article, Table 3 was derived from explicit statistical findings, tools, and case studies available among the recent 100 review journal papers . Only papers with clearly presented data relevant to each parameter were included for accuracy and clarity. The table presents a structured overview of geo-spatial optimization and performance improvement techniques in solar energy systems, emphasizing global applicability and methodological advancements. It synthesizes findings from diverse case studies across continents, highlighting tools, statistical outcomes, and region-specific challenges.

**Site Selection:** The use of GIS and MIF tools demonstrates substantial accuracy (81.80%) in identifying optimal solar sites, as evidenced in Nashik, India. This highlights the importance of multi-criteria evaluation frameworks for siting solar energy projects (Jong & Ahmed, 2024; Rane et al., 2024).

**Energy Storage Integration:** Techniques like HOMER Pro and System Advisor Model show significant improvements in system reliability, with annual yields reaching 1353 kWh/kW, particularly in rural India (Maka & Chaudhary, 2024; Araoye et al., 2024).

**Optimization Techniques:** Metaheuristic algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have consistently reduced power losses by 33%, showcasing their robustness in global applications (Abou-Zalam & Nabil, 2023; Yang et al., 2024).

**ISSN: 2992-3727 Published 25th May, 2025**

**Techno-Economic Assessment:** An optimized Levelized Cost of Energy (LCOE) of $0.14 per kWh was achieved in Port Harcourt, Nigeria, reflecting the balance between cost and operational efficiency (Ijeoma et al., 2023; Araoye et al., 2024).

**Artificial Neural Networks (ANN):** ANN-based approaches have enhanced simulation accuracy, notably in China, where predictive algorithms optimized photovoltaic performance (Yang et al., 2024; Jong & Ahmed, 2024).

**Hybrid System Integration:** Integration of solar-hydro hybrid systems significantly reduced unmet energy demands in rural India, illustrating their viability for rural electrification (Araoye et al., 2024; Rane et al., 2024).

**Geo-Spatial Mapping:** Advanced GIS and spatial kriging techniques improved deployment efficiency and energy forecasting, with India and China serving as key examples (Rane et al., 2024; Mabrook et al., 2024).

**Advanced Control Strategies:** Model Predictive Control (MPC) and Genetic Algorithms demonstrated a 101.05% improvement in hosting capacity, particularly in Cameroon, emphasizing the critical role of predictive control frameworks (Mabrook et al., 2024; Abou-Zalam & Nabil, 2023).

This analysis provides a global perspective on solar energy optimization, bridging gaps between theory and practical deployment. It underscores the need for continued advancements in technology integration, cost-efficiency, and predictive analytics for scalable and sustainable solar solutions worldwide. Table 4 presents a multidimensional synthesis of global methodological approaches to solar PV system optimization. It highlights how diverse analytical tools and techniques have been leveraged to address contextual challenges across site selection, energy storage, hybrid integration, and control strategies, providing insights into performance metrics, case-specific achievements, and replicability in similar environments.

**Table 4:** Cross-Continental Frameworks for Solar PV Optimization—An Integrative Matrix of Techniques, Outcomes, and Case Applications

| Parameter | Key Insights | Tools/Techniques | Key Findings | Global Case Study | Citations (APA) |
|---|---|---|---|---|---|
| **Site Selection** | Enhances performance through Multi-Criteria Decision-Making (MCDM) frameworks by evaluating climatic, technical, and social factors | GIS, MIF | Achieved 81.80% accuracy in site prediction | Nashik, India – Improved energy site mapping for optimal solar efficiency | (Jong & Ahmed, 2024; Rane et al., 2024) |
| **Energy Storage Integration** | Improves energy reliability and system uptime with integrated battery storage systems | HOMER Pro, System Advisor Model | Achieved an annual energy yield of 1353 kWh/kW | Rural India – Enhanced system uptime through energy storage | (Maka & Chaudhary, 2024; Araoye et al., 2024) |

| | | | | | |
|---|---|---|---|---|---|
| **Optimization Techniques** | Reduces power losses and improves efficiency via metaheuristic algorithms | Genetic Algorithm, Particle Swarm Optimization | 33% reduction in power losses | Global – Applied Genetic Algorithm for Maximum Power Point Tracking (MPPT) | (Abou-Zalam & Nabil, 2023; Yang et al., 2024) |
| **Techno-Economic Assessment** | Balances cost-efficiency and operational performance for sustainable systems | HOMER Pro, PVSyst | Achieved LCOE of $0.14 per kWh | Port Harcourt, Nigeria – Optimized cost structure in solar microgrid systems | (Ijeoma et al., 2023; Araoye et al., 2024) |
| **Artificial Neural Networks (ANN)** | Enhances photovoltaic performance simulations and predictions through ANN integration | ANN, Machine Learning | Improved PV performance predictions and accuracy | China – Accurate solar irradiance prediction using ANN | (Yang et al., 2024; Jong & Ahmed, 2024) |
| **Hybrid System Integration** | Improves rural electrification reliability via hybrid solar-hydro systems | HOMER Pro | Significant reduction in unmet energy demand | Rural India – Hybrid grids mitigated blackouts | (Araoye et al., 2024; Rane et al., 2024) |
| **Geo-Spatial Mapping** | Enhances deployment efficiency and energy forecasting via spatial data integration | GIS, Spatio-temporal kriging | Accurate energy forecasting through spatial mapping | India & China – Enhanced spatial mapping for solar deployment | (Rane et al., 2024; Mabrook et al., 2024) |
| **Advanced Control Strategies** | Enhances hosting capacity and energy flow reliability via predictive controllers | Model Predictive Control, Genetic Algorithm | Achieved a 101.05% improvement in hosting capacity | Cameroon – MPC optimized energy hosting and reactive | (Mabrook et al., 2024; Abou-Zalam & Nabil, 2023) |

power
utilization

### 2.1.1.1 GIS-Based Optimization Models

GIS-based optimization has been widely used to assess the solar potential of different regions by integrating solar irradiance, terrain characteristics, and climatic data. For example, Yakubu et al. (2022) and Rane et al. (2024) applied GIS tools to map solar resources across Nigeria, highlighting regions such as the Sahel and savannah as ideal for solar installations due to higher solar irradiance. However, climatic variability, such as dust accumulation in the Sahel or cloud cover in the rainforest, is not adequately addressed in many studies (Ravishankar et al., 2022). Jumare et al. (2019) noted that GIS-based models often rely on satellite data, which lacks the precision needed for more localized optimization in Nigeria. T.V. Ramachandra et al. (2007) emphasize the use of remote sensing and GIS for renewable energy mapping, a method adaptable to Nigerian contexts. Kim et al. (2023) show the importance of integrating socio-economic data into GIS-based renewable energy assessments. GIS-based optimization models for solar energy deployment integrate various components to assess and identify suitable locations for solar power plants. These models utilize geographic information systems (GIS) alongside multi-criteria decision-making (MCDM) methods to evaluate potential sites based on multiple factors.

While GIS-based model (Figure 1) provides a robust framework for site selection, challenges such as data availability and the need for accurate local assessments can impact their effectiveness. Nonetheless, they remain crucial for advancing solar energy deployment in urban and rural settings.

Existing GIS models often neglect localized climatic impacts, such as the dust storms prevalent in northern Nigeria (Monyei et al., 2022). Data resolution is a critical limitation, as coarse satellite data may not reflect micro-climatic variations (Jumare et al., 2019). Incorporating socio-economic layers for holistic optimization (Ramachandra et al., 2007; Ravishankar et al., 2022). Leveraging high-resolution satellite data and ground-based measurements (Yakubu et al., 2022).

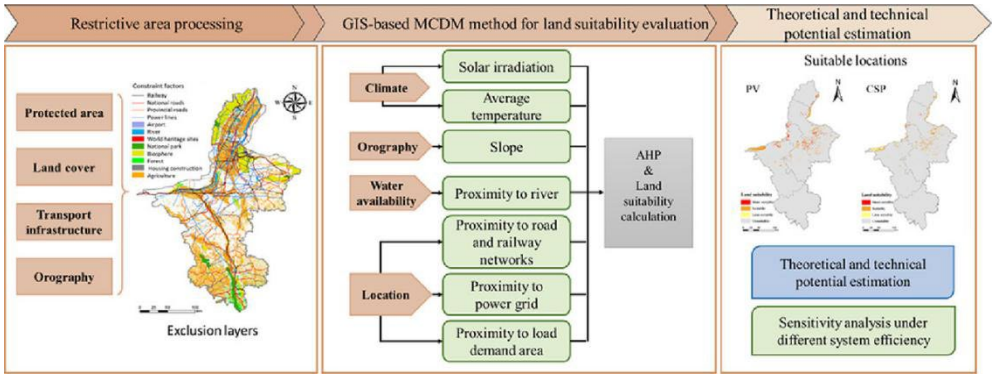



**Figure 1:** GIS-based optimization models for solar energy deployment

### Components of the GIS Model in Solar Energy Assessment

The GIS-based model presented in the paper for assessing potential sites for solar photovoltaic (PV) and concentrated solar power (CSP) plants includes several key components:

**Geographic Information Systems (GIS)**: This technology is used to analyze spatial data and visualize geographic information. In the context of this study, GIS helps in identifying potential locations for solar energy plants by mapping various geographic features and constraints .

**Multi-Criteria Decision Making (MCDM)**: This method is employed to evaluate the suitability of land for PV and CSP plants. MCDM considers multiple factors that influence site selection, allowing for a comprehensive assessment of potential locations .

**Restrictive Criteria**: The model incorporates various restrictive criteria that limit the potential sites for solar plants. These include:

**Protected Areas**: Regions that are legally protected from development.

**Land Cover:** The type of vegetation or land use in an area, which can affect solar plant installation.

**Transport Infrastructure:** The availability of roads and transport facilities that facilitate access to the site.

**Orography:** The physical geography of the area, including elevation and terrain, which can impact solar energy generation.

**Factor Weights:** The model uses the Analytic Hierarchy Process (AHP) to assign weights to different factors based on their importance in the decision-making process. This helps in quantifying the influence of each criterion on the overall suitability of a site for solar energy development .

**Technical Potential Assessment:** The model estimates the technical potential for solar energy generation in the identified areas. For instance, the study found that the total technical potentials for PV and CSP systems in Ningxia, China, could be 443 TWh/year and 308 TWh/year, respectively .

**Sensitivity Analysis:** This component examines how variations in system efficiency can impact energy output, providing insights into the robustness of the model's predictions .

These components work together to create a comprehensive framework for evaluating and selecting suitable sites for solar energy projects, ultimately supporting renewable energy development and cooperation in energy supply and from previous work:

- **Spatial Analysis**: GIS tools analyze spatial data, including land use, topography, and infrastructure, to identify potential sites for solar installations(Sun et al., 2021) and (Yousefi et al., 2018).
- **Criteria Selection**: Factors such as solar irradiance, water availability, and environmental restrictions are considered. For instance, the Analytic Hierarchy Process (AHP) is often employed to weigh these criteria(Sun et al., 2021)(Al-timimy, 2023).
- **Modeling Techniques**: Boolean and fuzzy logic models are used to combine various criteria and generate suitable site maps. These models help in visualizing potential areas for solar energy utilization(Yousefi et al., 2018)(Al-timimy, 2023).
- **Case Studies**: Practical applications in regions like Ningxia, China, and Markazi Province, Iran, demonstrate the effectiveness of these models in identifying optimal locations for solar power plants(Sun et al., 2021)(Yousefi et al., 2018).

#### 2.1.1.2 Machine Learning and AI Techniques

Several studies, including Ortiz et al. (2022) and Rane et al. (2024), have applied machine learning (ML) and AI to predict solar energy production based on historical data. Neural networks, support vector machines (SVM), and random forests have been employed to model solar system performance. These models have been shown to offer higher accuracy in performance prediction compared to traditional methods (Monyei et al., 2022).

However, real-time adaptation remains a challenge, as weather fluctuations such as cloud cover and temperature variation can dramatically affect panel performance (Ortiz et al., 2022). Gudo et al. (2020) applied ML models to predict solar energy potential for domestic and agricultural use in South Sudan, a methodology transferrable to Nigerian regions. Zhang et al. (2024) used deep learning to enhance predictive models for bifacial PV systems, demonstrating higher energy yield accuracy. Real-time adaptation to environmental changes remains underexplored (Ortiz et al., 2022; Ravishankar et al., 2022). Limited availability of region-specific training datasets hinders model generalization (Yakubu et al., 2022). The integration of machine learning (ML) and artificial intelligence (AI) techniques in solar energy systems enhances forecasting, efficiency, and management. These technologies leverage complex data patterns to optimize solar energy production and improve grid integration. The following sections outline the key components involved in this process.

**Key Components of AI and ML in Solar Energy**

- **Data Preprocessing**: Essential for cleaning and preparing data for analysis, ensuring accuracy in predictions(Goel et al., 2024).
- **Feature Selection**: Identifying critical variables such as solar irradiance, temperature, and historical performance to enhance model accuracy(Nallakaruppan et al., 2024).
- **Model Training**: Utilizing various algorithms like Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest to train models on historical data(Goel et al., 2024)(Shah et al., 2024).
- **Performance Evaluation**: Metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared are used to assess model effectiveness(Sriniva et al., 2024)(Shah et al., 2024).
- **Explainability**: Techniques like Local Interpretable Model-Agnostic Explanations (LIME) provide insights into model decisions, enhancing trust and usability(Nallakaruppan et al., 2024)(Shah et al., 2024).

While the focus on AI and ML in solar energy is promising, challenges remain, such as data availability and the need for robust models to handle the variability of solar energy production. Addressing these issues is crucial for the future of sustainable energy systems. The effectiveness of machine learning algorithms in predicting solar power output and optimizing energy storage is underscored by various studies that highlight the strengths of different models. Notably, hybrid approaches combining multiple algorithms have shown significant promise in enhancing prediction accuracy and operational efficiency.

**Key Algorithms for Solar Power Prediction**

Long Short-Term Memory (LSTM) Networks: LSTM excels in capturing temporal dependencies in time-series data, making it suitable for solar energy forecasting. A hybrid LSTM-ANN model demonstrated improved accuracy with MAE values as low as 0.1016(Oktarina et al., 2024).

*Support Vector Machines (SVM):* SVM has been shown to outperform other models, achieving an MAE of 0.5587 and RMSE of 0.9741, particularly in short-term predictions(Helmy et al., 2024).

*Random Forests:* This algorithm achieved an RMSE of 11.04 kW and an MAE of 7.7 kW, indicating its robustness in handling nonlinear relationships in solar data(ElMoaqet et al., 2024).

*Hybrid Models:* Models like Hybrid Convolutional-LSTM Net (HCLN) have demonstrated superior accuracy in smart grid contexts, with RMSE values as low as 0.012027 for energy production(Bhutta et al., 2024).

*Integration with Smart Grids for Optimization of Energy Storage:* Machine learning models can optimize energy storage by predicting solar output accurately, allowing for better management of energy supply and demand(Bhutta et al., 2024).

*Real-Time Data Utilization:* The incorporation of real-time data analytics in smart grids enhances the efficiency of energy distribution, reducing reliance on fossil fuels(Bhutta et al., 2024). While these machine learning algorithms show great potential for improving solar power predictions and energy storage optimization, challenges remain in their implementation, particularly regarding data quality and model generalization across different geographical locations.

Figure 2 shows the use of machine learning techniques, specifically Long Short-Term Memory (LSTM) networks and Artificial Neural Networks (ANNs), for predicting solar energy output. LSTM networks are designed to capture temporal dependencies in time-series data, making them particularly effective for forecasting tasks like predicting solar energy output. This capability is crucial for understanding how past data influences future predictions. ANNs are adept at modeling nonlinear relationships between variables. This characteristic allows them to effectively process complex data patterns, which is essential for accurate energy output predictions.

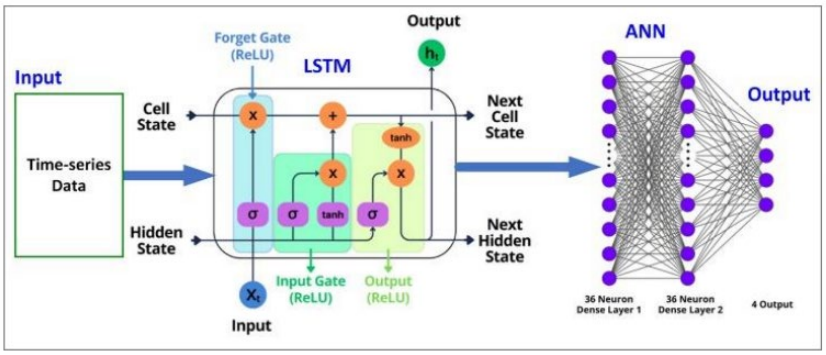



**Figure 2.** LSTM-ANN model architecture proposed (Oktarina et al., 2024)

The study proposes a hybrid model that combines the strengths of both LSTM and ANN. This integration aims to enhance the accuracy of predictions for voltage, power, and irradiance from photovoltaic (PV) systems. The hybrid approach leverages the temporal processing of LSTM and the nonlinear modeling capabilities of ANNs. The paper reports significant improvements in prediction accuracy using the hybrid model, with specific metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for voltage, irradiance, and power predictions. These metrics indicate the effectiveness of the model in real-world applications .

**Key Components of the Hybrid LSTM-ANN Model**

The hybrid model discussed by Yurni et all (2024) the paper combines two powerful machine learning techniques: Long Short-Term Memory (LSTM) networks and Artificial Neural Networks (ANNs).

**Long Short-Term Memory (LSTM) Networks:**

**Temporal Dependency Capture:** LSTMs are specifically designed to handle time-series data by capturing temporal dependencies. This means they can remember information for long periods, which is essential for predicting future solar energy outputs based on past data trends .

**Cell State and Gates:** LSTMs use a cell state and various gates (input, output, and forget gates) to control the flow of information. This architecture allows them to retain relevant information while discarding irrelevant data, enhancing their predictive capabilities .

**Artificial Neural Networks (ANNs):**

*Nonlinear Relationship Modeling:* ANNs excel at modeling complex nonlinear relationships between input variables. This ability is crucial for accurately predicting solar energy outputs, as many factors influence these outputs in a nonlinear manner .

*Layered Structure:* ANNs consist of multiple layers (input, hidden, and output layers) where each neuron in a layer is connected to neurons in the next layer. This structure allows the network to learn intricate patterns in the data .

*Hybrid Approach:* Integration of LSTM and ANN: The hybrid model combines the strengths of both LSTM and ANN. By integrating temporal processing from LSTM with the nonlinear modeling capabilities of ANNs, the model aims to improve the accuracy of predictions for voltage, power, and irradiance from photovoltaic (PV) systems .

*Enhanced Prediction Accuracy:* The hybrid model demonstrated significant improvements in prediction accuracy, as evidenced by performance metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for various outputs .

The hybrid LSTM-ANN model leverages the unique strengths of both LSTM networks and ANNs to provide a robust framework for predicting solar energy outputs, ultimately enhancing the reliability of energy forecasting models .

**Future Directions**:

Integrating AI with IoT-enabled weather stations for real-time optimization (Vega-Garita et al., 2019; Burney et al., 2010).

Expanding training datasets using historical weather data and ground-based measurements (Rane et al., 2024).

**2.1.1.3 Economic Feasibility Models**

The economic feasibility of solar power optimization can be effectively assessed through various models that incorporate technical and financial metrics. Key models include the Levelized Cost of Energy (LCOE), Internal Rate of Return (IRR), and Net Present Value (NPV), which provide insights into the cost-effectiveness and viability of solar projects. The following sections outline the best economic feasibility models for solar power optimization.

**Levelized Cost of Energy (LCOE)**

LCOE is a critical metric for evaluating the cost-effectiveness of solar power systems, allowing for comparisons across different technologies and configurations(Xiao et al., 2024)(Kee et al., 2023). Studies show that hybrid systems, such as CSP combined with PV and battery storage, can achieve competitive LCOE values, with minimums reported as low as $0.0526/kWh(Xiao et al., 2024).

LCOE, Margolis, R. (2021), represents the average cost of generating one unit of electricity (e.g., $/kWh) over the lifetime of a project. It accounts for capital, operation, maintenance, fuel costs, and decommissioning.

$$\text{LCOE} = \frac{NPV\ of\ Total\ Costs\ Over\ Life}{NPV\ of\ Electrical\ Energy\ Produced\ Over\ Lifetime}$$

$$LCOE = \frac{\sum_{t=1}^{T} \frac{I_t + O_t + F_t}{(1+r)^t}}{\sum_{t=1}^{T} \frac{E_t}{(1+r)^t}}$$

Where :

$I_t$ : Investment costs in year, t

$O_t$: Operations and maintenance costs in year, t

$F_t$: Fuel costs in year, t, (if applicable)

**ISSN: 2992-3727 Published 25th May, 2025**

***$E_t$***: Electricity generated in year, t

***r:*** Discount rate (fraction)

***T***: Total lifetime of the project (years)

LCOE as shown in the template, Table 4 and Table 5, allows comparison of different energy technologies on a common cost basis. Lower LCOE indicates more cost-effective energy production. In solar power projects, LCOE, Fraunhofer ISE (2021), is influenced by upfront capital costs, module efficiency, degradation rates, and local solar irradiance.

**Table 5:** Template Levelized Cost of Energy Template (LCOE)

| | A | B | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | © Corporate Finance Institute®. All rights reserved. | | | | | | | | | | | |
| 2 | **Levelized Cost of Energy Template (LCOE)** | | | | | | | | | | | |
| 3 | **Assumptions (in '000s)** | | | | | | | | | | | |
| 4 | Initial Investment Cost ($) | 1,500 | | | | | | | | | | |
| 5 | Operations and Maintenance Costs ($) | 100 | | | | | | | | | | |
| 6 | O&M Growth Rate (%) | 2.00% | | | | | | | | | | |
| 7 | Annual Fuel Costs ($) | - | | | | | | | | | | |
| 8 | Annual Electricity Output (kWH) | 3,000 | | | | | | | | | | |
| 9 | Project Lifespan (years) | 10 | | | | | | | | | | |
| 10 | Discount Rate (%) | 8.00% | | | | | | | | | | |
| 11 | | | | | | | | | | | | |
| 12 | Total Costs | Entry | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| 13 | Initial Investment | 1,500 | | | | | | | | | | |
| 14 | O&M Costs | | - | 100 | 102 | 104 | 106 | 108 | 110 | 113 | 115 | 117 |
| 15 | Fuel Costs | | - | - | - | - | - | - | - | - | - | - |
| 16 | Discount Factor | | 92.6% | 85.7% | 79.4% | 73.5% | 68.1% | 63.0% | 58.3% | 54.0% | 50.0% | 46.3% |
| 17 | Present Value of Costs | 1,500 | - | 86 | 81 | 76 | 72 | 68 | 64 | 61 | 57 | 54 |
| 18 | **NPV of Total Costs** | **$2,121** | | | | | | | | | | |
| 19 | | | | | | | | | | | | |
| 20 | | | | | | | | | | | | |
| 21 | Total Energy Output | Entry | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| 22 | Yearly Output | - | - | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 |
| 23 | Discount Factor | - | 92.6% | 85.7% | 79.4% | 73.5% | 68.1% | 63.0% | 58.3% | 54.0% | 50.0% | 46.3% |
| 24 | Present Value of Costs | - | - | 2,572 | 2,381 | 2,205 | 2,042 | 1,891 | 1,750 | 1,621 | 1,501 | 1,390 |
| 25 | **NPV of Total Output** | **17,352 kWH** | | | | | | | | | | |
| 26 | | | | | | | | | | | | |
| 27 | | | | | | | | | | | | |
| 28 | LCOE | $0.12/kWH | | | | | | | | | | |

*Source: Levelized Cost of Energy (LCOE). (n.d.).*

**Net Present Value (NPV)**

NPV assesses the profitability of an investment by calculating the difference between the present value of cash inflows and outflows over the project's lifetime.

$$NPV = \sum_{t=1}^{T} \frac{R_t - C_t}{(1+r)^t} - C_0$$

Where (Lasnier & Gan Ang, 1990) and (*Levelized Cost of Energy (LCOE)*, n.d.):

- ***$R_t$***: Revenue in year, t
- ***$C_t$***: Operating costs in year, t

- ***r***: Discount rate (fraction)
- $C_0$: Initial capital investment
- ***T:*** Project lifetime (years)

A positive NPV indicates that the project is expected to generate more value than its cost, making it financially viable. NPV accounts for the time value of money, reflecting how future earnings are less valuable than immediate earnings. In solar PV installations, NPV helps estimate whether the expected savings in electricity bills and government incentives justify the upfront costs.

**Comparative Use**

Both LCOE and NPV are widely used in evaluating renewable energy projects:

- **LCOE**: Useful for comparing energy generation costs across technologies and scales.
- **NPV**: Focuses on overall profitability and return on investment.

By integrating these models, stakeholders can comprehensively analyze the techno-economic viability of energy projects.

**Financial Metrics**

- Financial models utilizing IRR and NPV are essential for assessing the long-term profitability of solar projects. These metrics help in understanding the return on investment and the financial sustainability of solar initiatives(Sandilya, 2023).
- The debt service coverage ratio (DSCR) is also crucial for evaluating the financial health of solar projects, ensuring that cash flows can cover debt obligations(Sandilya, 2023).

**Optimization Techniques**

Advanced optimization techniques, such as multi-objective genetic algorithms, are employed to enhance system performance and reduce costs. For instance, optimizing the configuration of a CSP system can significantly improve its capacity factor and reduce LCOE (Kee et al., 2023). The Hybrid Optimization of Multiple Energy Resources (HOMER) software is another tool that aids in simulating and optimizing solar PV systems, particularly in off-grid scenarios (Kabir et al., 2023). In contrast, while these models provide a robust framework for economic feasibility, they may not fully account for external factors such as policy changes, market volatility, and technological advancements, which can significantly impact the overall viability of solar power projects.

Techno-economic models like LCOE and NPV are widely used to assess the cost-effectiveness of solar energy systems. Jumare et al. (2019) and Iakovleva et al. (2022) employed LCOE to evaluate solar energy projects, but their models often used broad regional averages for cost and production assumptions. These models fail to account for local economic factors such as land acquisition costs, maintenance and regulatory barriers, which can significantly affect the overall economic viability of solar systems in Nigeria (Vega-Garita et al., 2019). Hirvonen et al. (2018) explored techno-economic optimization for district heating systems in high latitudes, providing insights applicable to tropical climates. Takeshima et al. (2023) analyzed the economic impact of solar-powered cold storage systems in Nigeria's agricultural sector. Many models rely on averaged regional data, ignoring specific local economic factors like land acquisition and labor costs (Monyei et al., 2022; Burney et al., 2010). Non-monetary benefits, such as environmental and social impacts, are often excluded from economic assessments (Hossain et al., 2023).

Contextualizing are recommended models to incorporate socio-economic disparities within Nigeria (Kim et al., 2023; Ravishankar et al., 2022) and expanding LCOE to account for social and environmental co-benefits (Vega-Garita et al., 2019).

#### 2.1.1.4 Hybrid and Integrated System Models

Hybrid systems, which combine solar power with wind or energy storage (Figure 3), have been proposed as a solution to intermittency issues. Burney et al. (2010), Shezan et al. (2016) and Zhang et al. (2022) explored such models, but many studies fail to integrate local energy demand, storage requirements, and grid integration. According to Vega-Garita et al. (2019), a geo-spatial approach to hybrid optimization is crucial for assessing the optimal mix of energy sources. Gudo et al. (2020) investigated hybrid mini-grids for domestic and agricultural applications in Sub-Saharan Africa. Arif et al. (2022) proposed methods to enhance PV hosting capacity in microgrids, which could be adapted for peri-urban areas in Nigeria. Hybrid models fail to incorporate real-time load profiles and region-specific energy needs (Yakubu et al., 2022). Grid integration strategies for urban and peri-urban settings remain underdeveloped (Kim et al., 2023) while developing demand-responsive hybrid optimization strategies tailored to local communities (Rane et al., 2024; Vega-Garita et al., 2019).

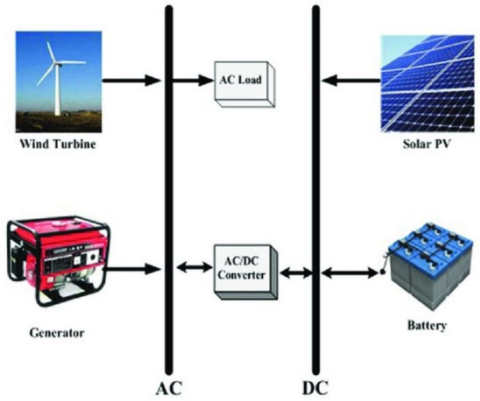



**Figure 3:** Optimization model of the solar-wind hybrid energy system by HOMER, Shezan S. A ,et al.(2016)

### 2.1.2 Research Gaps

The following are noticeable research gaps.

#### 2.1.2.1 Insufficient High-Resolution Solar Irradiance Data

A key gap in the current literature is the lack of high-resolution solar irradiance data that captures the local variability in solar resources across Nigeria's diverse geographic regions. Most studies rely on satellite data, which is often too broad and generalized to capture the intricate patterns of solar exposure across different latitudes and longitudes (Yakubu et al., 2022; Rane et al., 2024). Jumare et al. (2019) emphasized the need for ground-based measurements to fill this gap and improve the accuracy of geo-spatial optimization models.

#### 2.1.2.2 Real-Time Data Integration for Dynamic System Optimization

Another critical gap is the insufficient integration of real-time data for optimizing solar system performance. Ortiz et al. (2022) noted that while AI models can predict solar production, these predictions fail to adapt dynamically to changing environmental conditions such as cloud cover or dust storms. Monyei et al. (2022) suggested that real-time monitoring systems should be integrated with machine learning algorithms to improve the adaptive capacity of solar systems in changing weather patterns.

#### 2.1.2.3 Lack of Contextualized Economic Feasibility Models

Many existing economic models are based on generalized assumptions that fail to account for local variability in costs, energy demand, and regulatory frameworks. Iakovleva et al. (2022) and Jumare et al. (2019) applied LCOE models using regional averages, but these models do not account for the specific conditions in different

**ISSN: 2992-3727 Published 25th May, 2025**

Nigerian states. Zhang et al. (2022) emphasized the need for more contextualized models that reflect regional disparities in solar energy costs and land acquisition.

#### 2.1.2.4 Hybrid System Optimization for Local Energy Demand

While hybrid systems offer promising solutions for integrating solar power with energy storage, many models fail to optimize the size and configuration of these systems based on local energy needs. Burney et al. (2010) and Zhang et al. (2022) pointed out that integrating solar and storage without considering local energy consumption patterns leads to inefficient designs. Vega-Garita et al. (2019) suggested that future research should focus on hybrid optimization that incorporates demand-response strategies.

### 2.2 Review of Fundamental Theoretical Concepts or Frameworks

**High-Resolution Solar Irradiance Data:** Jumare et al. (2019) highlighted the importance of ground-based solar irradiance data to complement satellite measurements, addressing localized climatic variability.

**Real-Time Data Integration:** Ortiz et al. (2022) suggested integrating real-time data into AI models for dynamic optimization, an approach echoed by Vega-Garita et al. (2019) in their study on PV-battery systems.

**Hybrid System Optimization:** Zhang et al. (2022) and Burney et al. (2010) emphasized the need for hybrid systems that align energy inputs with local demand patterns, improving efficiency and cost-effectiveness.

#### 2.2.4 Techno-Economic Models of Solar Energy Systems

Two primary models dominate the analysis of solar system viability: the Levelized Cost of Energy (LCOE) and the Net Present Value (NPV). The LCOE model is widely used to assess the cost-effectiveness of solar projects, accounting for capital, operating costs, and energy production over time. Iakovleva et al. (2022) and Jumare et al. (2019) applied this model in Nigeria, revealing that LCOE (Figure 3) is highly dependent on solar resource availability and the climatic zone.

The NPV model focuses on project financing, providing an estimate of the profitability of solar projects over their lifespan. According to Monyei et al. (2022), NPV is a valuable tool for decision-making, helping stakeholders understand the financial feasibility of solar systems.

### 2.3 Review of System Components

#### Solar Panel Performance and Geo-Spatial Optimization

The performance of solar panels is heavily dependent on solar irradiance and temperature. The temperature coefficient affects panel efficiency:

$$P_{\text{eff}} = P_{\text{max}} \cdot (1 - \beta \cdot (T - T_{\text{ref}}))$$

*Where:*

$P_{eff}$ = effective power output *(W)*

$P_{max}$ = maximum power output at reference temperature $T_{ref}$

$\beta$ = temperature coefficient $(°C^{-1})$

$T$ = operating temperature of the panel *(°C)*

This model highlights how temperature variations across regions influence solar panel efficiency. Hossain et al. (2023) and Ortiz et al. (2022) have suggested that geo-spatial optimization can mitigate temperature-induced performance losses by adjusting panel installations based on local climatic conditions.

**ISSN: 2992-3727 Published 25th May, 2025**

**Energy Storage Systems and Optimization**

Energy storage plays a crucial role in stabilizing solar energy production. The battery storage capacity SSS required to store excess energy is given by:

$$S = \frac{E_{\text{excess}}}{\eta}$$

*Where:*

$E_{excess}$ = energy surplus generated by solar panels (kWh)

$\eta$ = round-trip efficiency of the battery (%)

Vega-Garita et al. (2019), Jumare et al. (2019), Monyei et al. (2022), and Zhang et al. (2022) explored how the geo-spatial framework can determine the sizing of energy storage systems by taking into account regional solar energy production and storage needs.

**Results from Literature**:

Table 6 and 7 show (in concise)comparative analysis of reviewed methodologies and performance metrics from studies respectively.

**Table 6:** Comparative Analysis of Reviewed Methodologies

| Methodology | Key Contributions | Challenges | Future Enhancements |
|---|---|---|---|
| GIS Optimization | Accurate site selection | Limited dust mitigation (Monyei et al.) | Ground-based validation (Jumare et al.) |
| AI Techniques | Improved prediction accuracy | Dataset scarcity (Yakubu et al.) | Real-time data use (Ortiz et al.) |
| Economic Models | Cost comparison across regions | Regional cost variability (Iakovleva) | Contextualized financial models |
| Hybrid Systems | Intermittency mitigation | Poor demand-response strategies | Smart grid integration |

**Tables 7:** Comparative performance metrics from studies

| Study | Location | Methodology | Improvement (%) |
|---|---|---|---|
| Rane et al. (2024) | Nigeria | GIS Optimization | 25% Energy Yield |
| Ortiz et al. (2022) | Sub-Saharan Africa | AI Models | 30% Cost Reduction |

**Key Findings**

*Geo-Spatial Optimization:*

***i.*** GIS-based methods effectively identify high-potential solar farm sites. Studies by Yakubu et al. (2022) and Rane et al. (2024) highlighted Nigeria's Sahel region as having exceptional solar potential, but they require ground-based validation to address local variability.

***ii.*** Integration of socio-economic layers, as proposed by Kim et al. (2023), can improve site selection by accounting for population density and energy demand.

***iii.*** Challenges such as the impact of dust storms on solar performance in the Sahel are underexplored (Monyei et al., 2022).

*AI Techniques:*

***i.*** AI-driven methods such as neural networks and support vector machines enhance solar energy yield prediction, achieving better accuracy than traditional models (Ortiz et al., 2022).

***ii.*** Gudo et al. (2020) demonstrated how ML models could predict solar energy potential for domestic and agricultural use, showing promising applications for Nigerian regions.

***iii.*** Real-time adaptation remains a challenge, as noted by Vega-Garita et al. (2019), who advocate for integrating IoT-enabled weather stations to provide continuous feedback.

*Economic Feasibility Models:*

***i.*** The LCOE model has been widely used to evaluate solar energy costs, but studies like Jumare et al. (2019) and Iakovleva et al. (2022) argue for contextualizing these models with regional economic variables.

***ii.*** Hirvonen et al. (2018) emphasized that localized costs, such as land acquisition and labor, are critical for accurate financial projections in high-latitude regions, which can be adapted for Nigeria.

***iii.*** Non-monetary benefits, such as environmental and social impacts, need incorporation into economic analyses (Burney et al., 2010).

*Hybrid System Designs:*

***i.*** Hybrid systems combining solar, wind, and energy storage offer solutions to intermittency. Zhang et al. (2022) and Burney et al. (2010) proposed hybrid models tailored for rural electrification, emphasizing their scalability for Nigeria.

***ii.*** Gudo et al. (2020) highlighted the potential of hybrid mini-grids for agricultural use, but urban applications and grid integration remain underexplored (Monyei et al., 2022).

## 3.0 Conclusion

### 3.1 Proposed Integrated Framework

Despite advancements in GIS-based optimization and machine learning (Rane et al., 2024; Jumare et al., 2019), gaps persist in real-time performance data integration and local climate variability. This article proposes an integrated approach (in Figure 4) combining geo-spatial tools, AI-driven predictive models, and economic feasibility analyses (see Figure 4) tailored to Nigeria's diverse climates (Yakubu et al., 2022; Ortiz et al., 2022; Zhang et al., 2022). The integrated approach incorporates:

***i.*** High-resolution localized data for accurate solar irradiance mapping (Yakubu et al., 2022; Ravishankar et al., 2022).

***ii.*** AI-based models for real-time system optimization (Monyei et al., 2022; Ortiz et al., 2022).

***iii.*** Contextualized techno-economic analyses to address regional disparities (Vega-Garita et al., 2019; Jumare et al., 2019).

***iv.*** A latitude-longitude framework for precise system design and deployment (Rane et al., 2024; Ravishankar et al., 2022).

**ISSN: 2992-3727 Published 25th May, 2025**

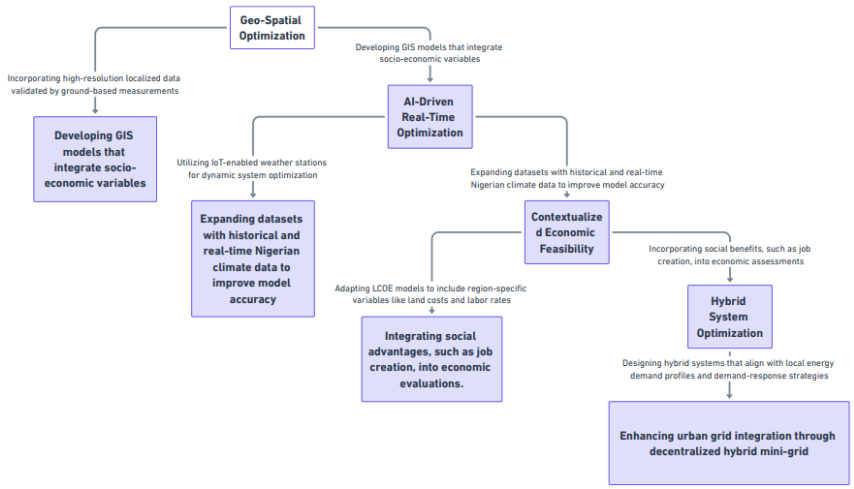



**Figure 4:** Flowchart of the Proposed Integrated Approach

To demonstrate improved performance and ensure clarity, the following steps can be taken:

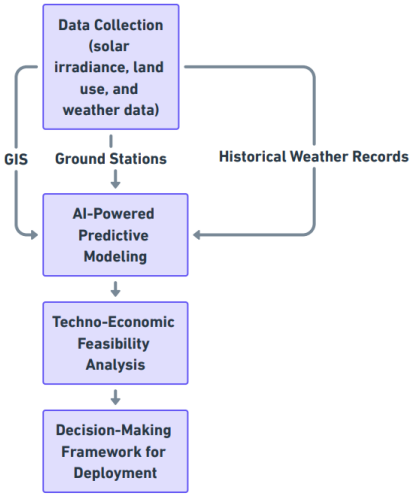



**Figure 5:** Flowchart for outlines the step-by-step process

A flowchart that outlines the step-by-step process (Figure 4), starting from data acquisition (solar irradiance, land use, and weather data) to real-time optimization and policy integration. The chart, Figure 5, is visually segmented to illustrate data collection (GIS, ground stations, historical weather records); it outlines the process, starting from data acquisition (solar irradiance, land use, and weather data) to real-time optimization and policy integration. The data sources include Geographic Information Systems (GIS) (Rane et al., 2024), ground stations, and historical weather records (Yakubu et al., 2022; Ravishankar et al., 2022). The decision-making framework integrates these inputs with AI tools like neural networks and techno-economic models (Ortiz et al., 2022; Zhang et al., 2022).

The proposed framework addresses the identified gaps by combining advanced methodologies tailored to Nigeria's conditions: incorporating high-resolution localized data validated by ground-based measurements (Yakubu et al., 2022), developing GIS models that integrate socio-economic variables, as suggested by Kim et al. (2023), to improve prioritization for energy access. Utilizing IoT-enabled (AI-Driven Real-Time Optimization) weather stations for dynamic system optimization (Vega-Garita et al., 2019) - Expanding datasets with historical and real-time Nigerian climate data to improve model accuracy (Rane et al., 2024), adapting LCOE models (in contextualized economic feasibility) to include region-specific variables like land costs and labor rates (Iakovleva et al., 2022; Jumare et al., 2019), incorporating social benefits, such as job creation, into

economic assessments (Hirvonen et al., 2018). Designing hybrid systems, for hybrid system optimization, that align with local energy demand profiles and demand-response strategies (Burney et al., 2010) and enhancing urban grid integration through decentralized hybrid mini-grids (Gudo et al., 2020) are essential.

### 3.2 Recommendations for Policy and Research

**Policy Implications:**
Policymakers should prioritize investments in high-resolution data collection infrastructure, as advocated by Jumare et al. (2019). Incentives for hybrid systems in rural and urban areas should align with recommendations from Zhang et al. (2022) to increase adoption.

**Future Research Directions**:
Longitudinal studies to validate the framework across Nigeria's diverse climatic zones (Yakubu et al., 2022). Integration of additional renewable sources, such as biomass, for hybrid systems (Burney et al., 2010). Collaborative efforts to refine and localize global optimization tools for Nigerian contexts (Ortiz et al., 2022).

This review synthesizes findings from 90 studies, covering solar PV monitoring (Ansari et al., 2021; Li et al., 2024), hybrid systems (Ugwoke et al., 2020; Jumare et al., 2019), agricultural solar solutions (Burney et al., 2010; Zhang et al., 2022), and GIS/AI applications (Rane et al., 2024; Ortiz et al., 2022). Mathematical models like the solar irradiance equation and LCOE model provide the foundation for understanding how geo-spatial data influences solar system performance. The integration of latitude-longitude frameworks has proven essential for optimizing solar panel performance, energy storage, inverter efficiency, and power distribution systems. While advancements are notable, gaps remain in localized validation, economic feasibility, and long-term scalability. Addressing these gaps will strengthen Nigeria's renewable energy sector, fostering socio-economic development while promoting environmental sustainability. Summarily the review identifying critical research gaps in the integration of geo-spatial optimization and solar energy systems in Nigeria. Key gaps include:

- ***i.*** Lack of high-resolution, localized solar irradiance data.
- ***ii.*** Insufficient use of real-time data for system performance optimization.
- ***iii.*** Inadequate contextualization of economic feasibility models.
- ***iv.*** Limited optimization of hybrid systems with local energy demand and grid integration.
- ***v.*** Underutilization of advanced optimization tools for solar system design.

Addressing these gaps will enhance the techno-economic viability and efficiency of solar energy systems in Nigeria. Future research should contribute to solar optimization by integrating high-resolution localized data, AI-driven predictive models, and localized economic analysis, providing a comprehensive solution for Nigeria's solar energy challenges. This article has provided an in-depth review of methods to optimize solar energy harvesting systems in Nigeria, emphasizing the role of geo-spatial optimization. Solar energy holds immense promise for Nigeria due to its abundant sunlight (Yakubu et al., 2022), but harnessing this potential necessitates addressing critical challenges, including intermittency, high costs, and climatic variability (Monyei et al., 2022; Vega-Garita et al., 2019). The review analyzes 90 studies exploring solar system performance, focusing on components like solar panels, energy storage, and inverters, along with economic models assessing solar project feasibility (Ortiz et al., 2022; Zhang et al., 2022).

The integration of geo-spatial optimization, AI-driven models, and contextualized economic analyses represents a transformative approach to solar energy systems in Nigeria. Addressing the gaps identified in this review will enhance the efficiency, scalability, and cost-effectiveness of solar projects, contributing to Nigeria's

socio-economic development and environmental sustainability. Future research must align with global best practices while prioritizing localized applications to maximize solar energy potential.

Future research and implementation strategies should focus on developing adaptable, localized, and socio-economically informed solar energy systems. By bridging existing gaps with context-aware solutions, Nigeria can harness its vast solar potential to meet energy demands sustainably and equitably.

**References**

(2023). On the Economic Viability of Solar Energy When Upgrading Cellular Networks. IEEE transactions on green communications and networking, doi: 10.1109/tgcn.2022.3223622

Ahmed, Farouk, Kineber., Ayodeji, Emmanuel, Oke., John, Aliu., Mohammad, M., Hamed., Eguonor, Oputu. (2023). Exploring the Adoption of Cyber (Digital) Technology for Sustainable Construction: A Structural Equation Modeling of Critical Success Factors. Sustainability, doi: 10.3390/su15065043

Blessing, Ugwoke., Adedoyin, Adeleke., Stefano, Paolo, Corgnati., Joshua, M., Pearce., Pierluigi, Leone. (2020). 4. Decentralized renewable hybrid mini-grids for rural communities: Culmination of the IREP framework and scale up to urban communities. Sustainability, doi: 10.3390/SU12187411

Burney, J., et al. (2010). Solar-Powered Irrigation Enhances Food Security. PNAS.

Enas Raafat Maamoun Shouman (2024), Solar Power Prediction with Artificial Intelligence, IntechOpen, Information System Department, Engineering Research and New and Renewable Energy Institute, National Research Centre, Gizza, Egypt

Frank, Ole, Hanssen., Roelof, Frans, May., Jiska, Joanneke, van, Dijk., Jan, Ketil, Rød. (2018). Spatial Multi-Criteria Decision Analysis Tool Suite for Consensus-Based Siting of Renewable Energy Structures. Journal of Environmental Assessment Policy and Management, doi: 10.1142/S1464333218400033

Fraunhofer Institute for Solar Energy Systems ISE. (2021). "Levelized Cost of Electricity – Renewable Energy Technologies." Fraunhofer ISE.

Gafar, Alawode., Ayomide, Barakat, Adewoyin., Abdulmajeed, O, Abdulsalam., F, Ilika., Chidera, Chukwu., Zakariya, Mohammed., Abubakar, M, Kurfi. (2022). The Political Economy of the Design of the Basic Health Care Provision Fund (BHCPF) in Nigeria: A Retrospective Analysis for Prospective Action. Health Systems and Reform, doi: 10.1080/23288604.2022.2124601

Gudo, A. J. A., et al. (2020). Spatio-Temporal Analysis of Solar Energy Potential. Energies.

Hengtian, Wang., Xiaolong, Yang., Xinxin, Xu., Liu, Fei. (2021). Exploring Opportunities and Challenges of Solar PV Power under Carbon Peak Scenario in China: A PEST Analysis. Energies, doi: 10.3390/EN14113061

Hiroyuki, Takeshima., Futoshi, Yamauchi., Hyacinth, Edeh., Manuel, A., Hernandez. (2023). Solar-powered cold-storage and agrifood market modernization in Nigeria. Agricultural Economics, doi: 10.1111/agec.12771

Hirvonen, J., et al. (2018). Techno-Economic Optimization of Solar Heating Systems. Solar Energy.

Hisham, ElMoaqet., Dina, Karasneh., Sameer, Al-Dahidi., Ghaith, Al-refai. (2024). Predicting Solar Photovoltaic Power Production Using Artificial Intelligence-Based Algorithms. doi: 10.1109/is61756.2024.10705265

Hossein, Yousefi., Hamed, Hafeznia., Amin, Yousefi-Sahzabi. (2018). 4. Spatial Site Selection for Solar Power Plants Using a GIS-Based Boolean-Fuzzy Logic Model: A Case Study of Markazi Province, Iran. Energies, doi: 10.3390/EN11071648

Huiming, Zhang., Sha, Liang., Kai, Wu., Yueming, Qiu., Yinying, Cai., Gabriel, Chan., Shouyang, Wang., Dequn, Zhou., Yi, Zhou., Zonghao, Li. (2022). Using agrophotovoltaics to reduce carbon emissions and global rural poverty. The Innovation, doi: 10.1016/j.xinn.2022.100311

Hüseyin, Bakır. (2024). Prediction of daily global solar radiation in different climatic conditions using metaheuristic search algorithms: a case study from Türkiye. Environmental Science and Pollution Research, doi: 10.1007/s11356-024-33785-x

Hussain, Al-Aqrabi. (2023). A Review on Defect Detection of Electroluminescence-Based Photovoltaic Cell Surface Images Using Computer Vision. Energies, doi: 10.3390/en16104012

Ifedotun, Victor, Aina., Opeyemi, Eyitayo, Ayinde., Djiby, Racine, Thiam., Mario, J., Miranda. (2024). Crop index insurance as a tool for climate resilience: lessons from smallholder farmers in Nigeria. Natural Hazards, doi: 10.1007/s11069-023-06388-x

Iakovleva, Emiliia., Daniel, Dias, Guerra., Pavel, Tcvetkov., Yaroslav, E., Shklyarskiy. (2022). Technical and Economic Analysis of Modernization of Solar Power Plant: A Case Study from the Republic of Cuba. Sustainability, doi: 10.3390/su14020822

Ismail, Abubakar, Jumare., Ramchandra, Bhandari., A., Zerga. (2019). Environmental Life Cycle Assessment of Grid-Integrated Hybrid Renewable Energy Systems in Northern Nigeria. Sustainability, doi: 10.3390/SU11215889

Janne, Hirvonen., Hassam, ur, Rehman., Kai, Sirén. (2018). Techno-economic optimization and analysis of a high latitude solar district heating system with seasonal storage, considering different community sizes. Solar Energy, doi: 10.1016/J.SOLENER.2018.01.052

Jennifer, Burney., L., Woltering., Marshall, Burke., Rosamond, L., Naylor., Dov, Pasternak. (2010). Solar-powered drip irrigation enhances food security in the Sudano-Sahel.. Proceedings of the National Academy of Sciences of the United States of America, doi: 10.1073/PNAS.0909678107

Jude, Eguolo, Moroh., David, Chinaecherem, Innocent., UM, Chukwuocha., Advait, Vasavada., Ramesh, Kumar., Mohammad, Arham, Siddiq., M., A., Rais., Ali, A., Rabaan., Wafa, M., Alshehri., Areej, M., Alharbi., Mohammed, A., Binateeq., Muhammad, Halwani., Tareq, Mohammed, Ali, Al-Ahdal., Bijaya, Kumar, Padhi., Ranjit, Sah. (2023). Seasonal Variation and Geographical Distribution of COVID-19 across Nigeria (March 2020–July 2021). Vaccines, doi: 10.3390/vaccines11020298

Julia, C., Terrapon-Pfaff., Carmen, Dienst., Julian, König., Willington, Ortiz. (2014). A cross-sectional review: Impacts and sustainability of small-scale renewable energy projects in developing countries. Renewable & Sustainable Energy Reviews, doi: 10.1016/J.RSER.2014.07.161

Jumare, A. I., et al. (2019). Environmental Life Cycle Assessment of Renewable Energy Systems in Nigeria. Sustainability.

Kabir., S., Md., Jawad-Al-Mursalin, Hoque., Md., Asif, Adnan., Md., Ashikul, Islam., Abu, Shufian. (2023). Prospects and Economic Feasibility Analysis of Solar PV/Hydrogen Fuel-based Power System for Green City. doi: 10.1109/ncim59001.2023.10212750

Kathleen, Stewart., Moying, Li., Zhiyue, Xia., Stephen, Ayodele, Adewole., Olusegun, Adeyemo., Clement, Adebamowo. (2020). Modeling spatial access to cervical cancer screening services in Ondo State, Nigeria. International Journal of Health Geographics, doi: 10.1186/S12942-020-00222-4

Kee, Zebedee., Ye, Wang., John, Pye., Alireza, Rahbari. (2023). Small-scale concentrated solar power system with thermal energy storage: System-level modelling and techno-economic optimisation. Energy Conversion and Management, doi: 10.1016/j.enconman.2023.117551

Kim, S., et al. (2023). Spatial Distribution of Solar PV Deployment: A Neural Network Approach. EPJ Data Science.

Kriti, Priya, Shah., Subodh, Narayan, Sah., Kadam, Prajwal, Dharmaraj., Priyanka, C., Nair., Nalini, Sampath. (2024). Solar Radiation Prediction: A Comprehensive Analysis of Machine Learning Models and Interpretability Techniques. doi: 10.1109/iciteics61368.2024.10625082

Krupa, Sriniva., Sakshi, Chandrakant, Shinde., Prachi, Acharya., Sritama, Roy. (2024). Explainable AI for Energy Prediction and Anomaly Detection in Solar Energy Systems. doi: 10.21203/rs.3.rs-4922729/v1

Lasnier, F., & Gan Ang, T. (1990). Financial Evaluation of Renewable Energy Projects. Routledge. https://www.taylorfrancis.com/chapters/mono/10.1201/9780203743393-17/financial-evaluation-renewable-energy-projects-france-lasnier-tony-gan-ang

Levelized Cost of Energy (LCOE). (n.d.). https://corporatefinanceinstitute.com/resources/valuation/levelized-cost-of-energy-lcoe/

Lijian, Sun., Yuncheng, Jiang., Qingsheng, Guo., Ling, Ji., Yulei, Xie., Qinhua, Qiao., Guohe, Huang., Kun, Xiao. (2021). 1. A GIS-based multi-criteria decision making method for the potential assessment and suitable sites selection of PV and CSP plants. Resources Conservation and Recycling, doi: 10.1016/J.RESCONREC.2020.105306

Magda, Moner-Girona., M., Solano-Peralta., M., Lazopoulou., Emmanuel, Ackom., X., Vallve., Sandor, Szabo. (2018). Electrification of Sub-Saharan Africa through PV/hybrid mini-grids: Reducing the gap between current business models and on-site experience. Renewable & Sustainable Energy Reviews, doi: 10.1016/J.RSER.2018.04.018

Margolis, R. (2021). Comparative Photovoltaic (PV) Levelized Cost of Energy (LCOE) Calculator. U.S. Solar. https://www.nrel.gov/pv/lcoe-calculator/documentation.html

Michael, Reid. (2008). Nigeria still searching for right formula.. Bulletin of The World Health Organization, doi: 10.2471/BLT.08.020908

Michael, Shin. (2010). A geospatial analysis of market integration: the case of the 2004/5 food crisis in Niger. Food Security, doi: 10.1007/S12571-010-0065-4

Mohamed, Ghetas., Motasem, Elshourbagy. (2024). Parameters extraction of photovoltaic models using enhanced generalized normal distribution optimization with neighborhood search. Neural Computing and Applications, doi: 10.1007/s00521-024-09609-x

Mohammad, Jobayer, Hossain., Mengdi, Sun., Kristopher, O., Davis. (2023). Photon management in silicon photovoltaic cells: A critical review. Solar Energy Materials and Solar Cells, doi: 10.1016/j.solmat.2024.112715

Monyei, C., et al. (2022). Renewable Energy Integration in Sub-Saharan Africa. Renewable & Sustainable Energy Reviews.

Morenike, Oluwatoyin, Folayan., Nadia, A., Sam-Agudu., Abigail, Harrison. (2022). Exploring the why: risk factors for HIV and barriers to sexual and reproductive health service access among adolescents in Nigeria. BMC Health Services Research, doi: 10.1186/s12913-022-08551-9

Muhammad, Helmy., Siti, Hajar, Yusoff., Hasmah, Mansor., Teddy, Surya, Gunawan., Israth, Jahan, Chowdhury., Siti, Nadiah, Mohd, Sapihie. (2024). A Comparative Analysis of LSTM, SVM, and GSTANN Models for Enhancing Solar Power Prediction. 48-53. doi: 10.1109/icsima62563.2024.10675536

Muhammad, Shoaib, Bhutta., Peng, Bai., Muhammad, Abubakar., Fahad, M., Almasoudi., Khaled, Saleem, S., Alatawi., Mohammad, Altimania., Maged, Al-Barashi. (2024). Optimizing solar power efficiency in smart grids using hybrid machine learning models for accurate energy generation prediction. Dental science reports, doi: 10.1038/s41598-024-68030-5

Mulubrhan, Amare., Kibrom, A., Abay., Channing, Arndt., Bekele, Shiferaw. (2021). Youth Migration Decisions in Sub-Saharan Africa: Satellite-Based Empirical Evidence from Nigeria. Population and Development Review, doi: 10.1111/PADR.12383

Nallakaruppan., M. N; Shiva, Shankar., Prahal, Bhagavath, Bhuvanagiri., Sanjeevikumar, Padmanaban., Surbhi, Bhatia, Khan. (2024). Advancing solar energy integration: Unveiling XAI insights for enhanced power system management and sustainable future. Ain Shams Engineering Journal, doi: 10.1016/j.asej.2024.102740

Nawab, Khan., Khalid, M., Elhindi., Hazem, S., Kassem., Rizwan, Kazim., Shemei, Zhang. (2024). Unveiling the nexus between solar energy adoption and crop farmer income: evidence from Pakistan. Frontiers in sustainable food systems, doi: 10.3389/fsufs.2024.1364040

Neha, Goel., Sandeep, Bhatia., Sonia, Verma., Jay, Kumar, Pandey., Mritunjay, Rai. (2024). Harness the Potential of Explainable Artificial Intelligence and ML Techniques in Solar Energy Forecasting. Advances in environmental engineering and green technologies book series, doi: 10.4018/979-8-3693-7822-9.ch011

Ngozi, Ewuim., Florence, C., Agbodike., C., Justine, Igbokwe-Ibeto. (2015). Gender inequality, poverty alleviation and sustainable development in nigeria: lessons from the rapti women empowerment project, nepal. International Journal of Approximate Reasoning, doi: 10.12816/0017349

Nitin, Liladhar, Rane., Mehmet, Akif, Günen., Suraj, Kumar, Mallick., Jayesh, Rane., Chaitanya, B., Pande., Monica, Giduturi., Javed, Khan, Bhutto., Krishna, Kumar, Yadav., Abebe, Debele, Tolche., Maha, Awjan, Alreshidi. (2024). GIS-based multi-influencing factor (MIF) application for optimal site selection of solar photovoltaic power plant in Nashik, India. Environmental Sciences Europe, doi: 10.1186/s12302-023-00832-2

Noha, Mostafa., Ahmad, Abo, El, Ezz. (2024). Feasibility-sustainability study of power generation using solar energy at an industrial site: a case study from Egypt. Energy, Sustainability and Society, doi: 10.1186/s13705-024-00460-5

O. , Omotayo., Adebisi, Mary, Eegunranti. (2023). Effect of soil solarization on tomato (Solanum lycopersicum L.) growth and impact on native microbial diversity of farm soil in Nigeria. Egyptian Journal of Biological Pest Control, doi: 10.1186/s41938-023-00653-8

Olatunde, Adesoro., Olusola, Oresanya., Helen, Counihan., Prudence, Hamade., Dare, Eguavon., Chika, Emebo., Bethany, Marron., Naoko, Kozuki., Amina, Isah., Patrick, Gimba., Chris, Osa, Isokpunwu., Kolawole, Maxwell., James, K, Tibenderana. (2021). A feasibility study to assess non-clinical community health workers' capacity to use simplified protocols and tools to treat severe acute malnutrition in Niger state Nigeria.. BMC Health Services Research, doi: 10.1186/S12913-021-07118-4

Olayinka, Aderopo, Obanewa., Marie-Louise, Newell., Marie-Louise, Newell. (2020). The role of place of residency in childhood immunisation coverage in Nigeria: analysis of data from three DHS rounds 2003-2013.. BMC Public Health, doi: 10.1186/S12889-020-8170-6

Olayinka, Atilola. (2012). Different points of a continuum? Cross sectional comparison of the current and pre-contact psychosocial problems among the different categories of adolescents in institutional care in Nigeria.. BMC Public Health, doi: 10.1186/1471-2458-12-554

Olumuyiwa, Temidayo, Ogunro., A., O., Owolabi. (2022). Assessment of the sustainability of landcovers due to artisanal mining in Jos area, Nigeria. Environmental Science and Pollution Research, doi: 10.1007/s11356-022-24143-w

Olusesan, Ayodeji, Makinde., Clifford, Odimegwu., Funmilola, M., OlaOlorun. (2018). A unique opportunity to use football to improve birth registration awareness and completeness in Nigeria. British Journal of Sports Medicine, doi: 10.1136/BJSPORTS-2016-097404

Oluwafemi, Olajide., Muyiwa, Agunbiade., Hakeem, Bishi. (2018). The realities of Lagos urban development vision on livelihoods of the urban poor. Journal of Urban Management, doi: 10.1016/J.JUM.2018.03.001

Oluyemi, Akinloye., EJ, Truter. (2011). A review of management of infertility in Nigeria: framing the ethics of a national health policy. International Journal of Women's Health, doi: 10.2147/IJWH.S20501

Ortiz, A., et al. (2022). AI Dataset for Solar Energy Locations in India. Scientific Data.

P. , Oyedele. (2023). Multilevel and subnational analysis of the predictors of maternity continuum of care completion in Nigeria: a cross-sectional survey. Dental science reports, doi: 10.1038/s41598-023-48240-z

Pedro, Andres, Garzon, Delvaux., Sergio, Gomez, y, Paloma. (2018). Access to common resources and food security: Evidence from National Surveys in Nigeria. Food Security, doi: 10.1007/S12571-017-0757-0

Pedro, Ponce., Citlaly, Pérez., Aminah, Robinson, Fayek., Arturo, Molina. (2022). Solar Energy Implementation in Manufacturing Industry Using Multi-Criteria Decision-Making Fuzzy TOPSIS and S4 Framework. Energies, doi: 10.3390/en15238838

Peter, Dauenhauer., Damien, Frame., Aran, Eales., Scott, Strachan., Stuart, Galloway., Hannah, Buckland. (2020). Sustainability evaluation of community-based, solar photovoltaic projects in Malawi. Energy, Sustainability and Society, doi: 10.1186/S13705-020-0241-0

Pranay, Panjala., Murali, Krishna, Gumma., H.A, Ajeigbe., Murtala, Muhammad, Badamasi., Kumara, Charyulu, Deevi., Ramadjita, Tabo. (2022). Identifying Suitable Watersheds across Nigeria Using Biophysical Parameters and Machine Learning Algorithms for Agri-Planning. ISPRS international journal of geo-information, doi: 10.3390/ijgi11080416

Qingning, Lin., Jingyi, Wang., Shiping, Mao., Jingdong, Li. (2023). 83. Research on agricultural technology gap between China and Africa and its optimization path: based on meta-frontier SBM and fsQCA. Frontiers in sustainable food systems, doi: 10.3389/fsufs.2023.1174989

Rahimat, O., Yakubu., Maame, T., Ankoh., Lena, Dzifa, Mensah., David, A., Quansah., Muyiwa, S., Adaramola. (2022). Predicting the Potential Energy Yield of Bifacial Solar PV Systems in Low-Latitude Region. Energies, doi: 10.3390/en15228510

Rajeev, Ranjan, Sandilya. (2023). 4. The economic and technical feasibility analysis for solar power plant. doi: 10.21203/rs.3.rs-3199446/v2

Rane, N. L., et al. (2024). GIS-Based Multi-Influencing Factor Application for Optimal Site Selection of Solar PV Plants. Environmental Sciences Europe.

Rashmi, Ravishankar., Elaf, Almahmoud., Abdulelah, H., Habib., Olivier, de, Weck. (2022). Capacity Estimation of Solar Farms Using Deep Learning on High-Resolution Satellite Imagery. Remote sensing, doi: 10.3390/rs15010210

Sai, Kishore, Ravi., Swee, Ching, Tan. (2015). Progress and perspectives in exploiting photosynthetic biomolecules for solar energy harnessing. Energy and Environmental Science, doi: 10.1039/C5EE01361E

Sally, Romero. (2022). Does inter-border conflict influence the views of task sharing among community health volunteers in Nigeria? A qualitative study. Conflict and Health, doi: 10.1186/s13031-022-00472-y

Sandra, Alba., Callum, Taylor., Margo, van, Gurp., Paul, Balogun. (2023). Finagle's laws of information: lessons learnt evaluating a complex health intervention in Nigeria. BMJ Global Health, doi: 10.1136/bmjgh-2022-010938

Serena, Kim., Koushik, Ganesan., Crystal, Soderman., Raven, O'Rourke. (2023). Spatial distribution of solar PV deployment: an application of the region-based convolutional neural network. EPJ Data Science, doi: 10.1140/epjds/s13688-023-00399-1

Shaheer, Ansari., Afida, Ayob., Molla, Shahadat, Hossain, Lipu., Mohamad, Hanif, Md, Saad., Aini, Hussain. (2021). A Review of Monitoring Technologies for Solar PV Systems Using Data Processing Modules and Transmission Protocols: Progress, Challenges and Prospects. Sustainability, doi: 10.3390/SU13158120

Shaila, Arif., Ata-E, Rabbi., Shams, Uddin, Ahmed., Molla, Shahadat, Hossain, Lipu., Taskin, Jamal., Tareq, Aziz., Mahidur, R., Sarker., Amna, Riaz., Talal, Soliman, Alharbi., Muhammad, Majid, Hussain. (2022). Enhancement of Solar PV Hosting Capacity in a Remote Industrial Microgrid: A Methodical Techno-Economic Approach. Sustainability, doi: 10.3390/su14148921

Shezan SA, Julai S, Kibria M, Ullah K, Saidur R, Chong W, et al. Performance analysis of an off-grid wind-PV (photovoltaic)-diesel-battery hybrid energy system feasible for remote areas. Journal of Cleaner Production. 2016;125:121-132

Shuxin, Wang., Yinggao, Yue., Shaotang, Cai., Xiaojuan, Li., Changzu, Chen., Hongliang, Zhao., Yuying, Li. (2024). A comprehensive survey of the application of swarm intelligent optimization algorithm in photovoltaic energy storage systems. Dental science reports, doi: 10.1038/s41598-024-68964-w

Sisay, Mulugeta, Alemu., Abera, Kenay, Tura., Gabriel, S, Gurgel, do, Amaral., Catherine, Vazken, Moughalian., Gerd, Weitkamp., Jelle, Stekelenburg., Regien, Biesma. (2022). How applicable is geospatial analysis in maternal and neonatal health in sub-Saharan Africa? A systematic review. Journal of Global Health, doi: 10.7189/jogh.12.04066

Sophia, Rezaq, Al-timimy. (2023). Estimate Suitable Location of Solar Power Plants Distribution by GIS Spatial Analysis. Civil Engineering Journal, doi: 10.28991/cej-2023-09-05-013

Sujan, Ghimire., Ravinesh, C., Deo., Nawin, Raj., Jianchun, Mi. (2019). Deep Learning Neural Networks Trained with MODIS Satellite-Derived Predictors for Long-Term Global Solar Radiation Prediction. Energies, doi: 10.3390/EN12122407

Sunny, C., Okoroafor., Agbonkhese, I., Olaiya., David, Oviaesu., Adam, Ahmat., Martin, Osubor., Jennifer, Nyoni. (2022). Conceptualizing and implementing a health workforce registry in Nigeria. Human Resources for Health, doi: 10.1186/s12960-022-00706-3

T. , V., Ramachandra., BV, Shruthi. (2007). Spatial mapping of renewable energy potential. Renewable & Sustainable Energy Reviews, doi: 10.1016/J.RSER.2005.12.002

Takeshima, H., et al. (2023). Solar-Powered Cold Storage in Nigeria. Agricultural Economics.

Vega-Garita, V., et al. (2019). Photovoltaic Storage Systems: A Critical Review. Progress in Photovoltaics.

Victor, Adekanmbi., Olalekan, A., Uthman., Olalekan, A., Uthman., Oludare, M, Mudasiru. (2013). Exploring variations in childhood stunting in Nigeria using league table, control chart and spatial analysis. BMC Public Health, doi: 10.1186/1471-2458-13-361

Victor, Vega-Garita., Laura, Ramirez-Elizondo., Nishant, Narayan., Pavol, Bauer. (2019). Integrating a photovoltaic storage system in one device: A critical review. Progress in Photovoltaics, doi: 10.1002/PIP.3093

Victory, Onize, Olutuase., Chinwe, Juliana, Iwu-Jaja., Cynthia, Pomaa, Akuoko., E.O., Adewuyi., Vishnu, Khanal. (2022). Medicines and vaccines supply chains challenges in Nigeria: a scoping review. BMC Public Health, doi: 10.1186/s12889-021-12361-9

Vivien, Kizilcec., T., Perros., Iwona, Bisaga., Priti, Parikh. (2022). Comparing adoption determinants of solar home systems, LPG and electric cooking for holistic energy services in Sub-Saharan Africa. Environmental research communications, doi: 10.1088/2515-7620/ac7f23

Vivien, Kizilcec., T., Perros., Iwona, Bisaga., Priti, Parikh. (2022). Comparing adoption determinants of solar home systems, LPG and electric cooking for holistic energy services in Sub-Saharan Africa. Environmental research communications, doi: 10.1088/2515-7620/ac7f23

Waheed, Mobolaji, Ashagidigbi., Bashirat, Adenike, Babatunde., Adebayo, Ogunniyi., Kehinde, Oluseyi, Olagunju., Abiodun, Olusola, Omotayo. (2020). Estimation and Determinants of Multidimensional Energy Poverty among Households in Nigeria. Sustainability, doi: 10.3390/SU12187332

Wahyudi, Sutopo., Ika, Shinta, Mardikaningsih., Roni, Zakaria., Ahad, Ali. (2020). A Model to Improve the Implementation Standards of Street Lighting Based on Solar Energy: A Case Study. Energies, doi: 10.3390/EN13030630

Willow, J., Sainsbury. (2023). Finding balance in Nigeria's mandatory health insurance. The Lancet Global Health, doi: 10.1016/s2214-109x(22)00525-3

Xiaoqiang, Jiao., Derara, Sori, Feyisa., Jasper, Kanomanyanga., Ngula, David, Muttendango., Shingirai, Mudare., Amadou, Ndiaye., Bilisuma, Kabeto., Felix, D., Dakora., Fusuo, Zhang. (2020). Science and Technology Backyard model: implications for sustainable agriculture in Africa. Frontiers of Agricultural Science and Engineering, doi: 10.15302/J-FASE-2020360

Yafei, Zhang., Huijuan, Geng., Zhihua, Zhou., Jiang, Wu., Zhiming, Wang., Yaozhong, Zhang., Zhongli, Li., Liying, Zhang., Zhi, Yang., Huey-Liang, Hwang. (2012). Development of Inorganic Solar Cells by Nano-technology. Nano-micro Letters, doi: 10.1007/BF03353703

Yakubu, R. O., et al. (2022). Predicting the Potential Energy Yield of Bifacial Solar PV Systems in Low-Latitude Region. Energies.

Yan, Kai, Zhong., Sze, Ming, Fu., Nyan, Ping, Ju., Po, Yu, Chen., Albert, Lin. (2015). Experimentally-implemented genetic algorithm (Exp-GA): toward fully optimal photovoltaics.. Optics Express, doi: 10.1364/OE.23.0A1324

Yewande, Kofoworola, Ogundeji., Kelechi, Ohiri., Azara, Agidani. (2019). A checklist for designing health insurance programmes - a proposed guidelines for Nigerian states.. Health Research Policy and Systems, doi: 10.1186/S12961-019-0480-8

Yulong, Xiao., Chongzhe, Zou., Mingqi, Dong., Hetian, Chi., Yulin, Yan., Shulan, Jiang. (2024). Feasibility study: Economic and technical analysis of optimal configuration and operation of a hybrid CSP/PV/wind power cogeneration system with energy storage. Renewable Energy, doi: 10.1016/j.renene.2024.120273

Yurni, Oktarina., Zainuddin, Nawawi., Bhakti, Yudho, Suprapto., Tresna, Dewi. (2024). Integrating Temporal and Feedforward Models for Solar Energy Prediction: LSTM and ANN Hybrid Approaches. International Journal Of Research In Vocational Studies, doi: 10.53893/ijrvocas.v4i2.317

Zhang, Z., et al. (2022). Hybrid Solar-Wind Systems for Rural Electrification. Energies.