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Design and Performance Analysis of a Solar-Powered Smart Energy Management System for Rural Electrification in Nigeria

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Abstract- Nigeria's rural areas continue to experience severe electricity access deficits, with rural grid penetration below 30 percent and average urban supply availability of only six to seven hours daily. This paper examines the design architecture, control logic, and performance characteristics of a solar-powered smart energy management system (SEMS) developed to address this gap through decentralised, intelligence-driven electrification. Evidence from the photovoltaic engineering, microgrid control, Internet of Things (IoT), and artificial intelligence literature is synthesised to propose an integrated architecture comprising a photovoltaic generation subsystem, hybrid lithium-ion/lead-acid battery storage, a microcontroller-based smart energy management unit, IoT-enabled remote monitoring, and machine-learning-based load forecasting and demand-side management. Maximum power point tracking (MPPT) strategies, charge controller topologies, and communication protocols suited to low-bandwidth rural environments are critically analysed. A techno-economic and reliability framework, informed by HOMER-based case studies from comparable Nigerian rural contexts, evaluates system sizing, levelised cost of electricity, loss-of-power probability, and renewable energy fraction. Hybrid fuzzy-logic-enhanced MPPT controllers combined with predictive load scheduling can improve system efficiency by 12 to 25 percent relative to conventional fixed-threshold control, while IoT-based demand-side management can reduce peak load by 40 to 76 percent through adaptive appliance prioritisation. Barriers to large-scale deployment, including financing gaps, technical capacity, quality assurance, and policy inconsistency, are evaluated, and a replicable framework for scaling smart solar microgrids across Nigeria's agro-climatic zones is proposed.

Index Terms— Artificial Intelligence, Internet of Things, Microgrid, Nigeria, Rural Electrification, Smart Energy Management, Solar Photovoltaic Systems.

I. INTRODUCTION

Access to reliable electricity remains one of the most persistent development challenges confronting Nigeria, Africa's most populous nation. The World Bank's 2025 Tracking SDG7 report found that Nigeria has the largest absolute electricity access deficit of any country in the world, with an estimated 86.8 million citizens lacking access to grid electricity even as national access stood at approximately 61 percent in 2023 [63]. The urban-rural disparity is stark: urban access approaches 84 percent while rural access lingers at only 24 to 26 percent [49]. Where rural grid connections exist, reliability is frequently compromised, with households reporting an average of seven power outages weekly and outages of up to twelve hours, forcing widespread dependence on costly, polluting petrol and diesel generators [17, 36]. This persistent energy poverty imposes substantial socio-economic costs. Unreliable power constrains agro-processing, healthcare delivery, education, small-enterprise productivity, and digital inclusion in rural communities, and is estimated to cost the Nigerian economy 5 to 7 percent of GDP annually, approximately US$25 billion [62]. Nigeria's vast and dispersed rural settlement pattern renders conventional transmission and distribution infrastructure economically unviable for many communities, making decentralised solar photovoltaic (PV) microgrids and solar home systems the most technically and economically feasible pathway to universal electrification [35, 32].

Nigeria possesses abundant solar resources well suited to decentralised generation. Northern Nigeria receives between 5.62 and 7.01 kWh/m² of daily solar irradiation, while southern Nigeria receives 3.54

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to 5.43 kWh/m² [38, 53]. The northeast geopolitical zone possesses the highest annual mean global solar radiation in the country, approximately 2,179.5 kWh/m²/year [64]. This abundance is concentrated precisely in the regions with the lowest grid electrification rates and most acute rural energy poverty, including Borno, Yobe, Sokoto, and Zamfara States, presenting a compelling rationale for solar-based electrification.

Conventional standalone solar PV systems in rural Nigeria have frequently underperformed due to inadequate sizing, poor maximum power point tracking, inefficient battery utilisation, absence of remote fault diagnosis, and lack of intelligent demand-side management to match variable generation with load [13, 35]. Smart energy management systems (SEMS), integrating embedded control electronics, IoT sensing and communication, and artificial intelligence (AI)-based forecasting and optimisation, offer a pathway to substantially improve the technical performance, economic viability, and resilience of solar-powered rural electrification [30], transforming a passive installation into an adaptive cyber-physical system capable of forecasting generation and demand, prioritising critical loads, detecting faults remotely, and optimising battery dispatch in real time.

This paper presents a design and performance analysis of a solar-powered SEMS tailored to rural Nigeria's technical, economic, and infrastructural realities. Its objectives are: (i) to critically review the state of the art in solar PV technology, energy storage, IoT-enabled monitoring, and AI-based load forecasting and demand-side management as applied to rural microgrid electrification; (ii) to propose an integrated system architecture and control methodology for a smart energy management unit suited to low-bandwidth, resource-constrained rural environments; (iii) to evaluate the techno-economic and reliability performance of the proposed system using sizing and cost parameters drawn from comparable Nigerian case studies; and (iv) to critically analyse deployment barriers and propose a replicable framework for national scale-up.

II. LITERATURE REVIEW

A. Global and Regional Context of Rural Electrification

Globally, the number of people without electricity access stabilised at around 600 million in 2023, following a temporary increase from the COVID-19 pandemic and the global energy crisis triggered by the war in Ukraine [26]. Sub-Saharan Africa now accounts for approximately 85 percent of the global electricity access deficit, up from 50 percent in 2010, with population growth outpacing new electrification [26, 63]. The IEA estimates approximately 135 million new connections are required annually from 2024 onward to achieve universal access by 2030, far exceeding current deployment rates [26]. In response, the World Bank and African Development Bank launched the Mission 300 initiative, targeting electricity access for 300 million Sub-Saharan Africans by 2030 through grid densification, mini-grids, and standalone solar systems, with an estimated funding requirement exceeding US$90 billion [63].

Mini-grids and solar home systems are increasingly recognised as the least-cost electrification option for most unserved rural populations. Comparative geospatial least-cost planning studies consistently show mini-grid and standalone solar PV solutions are more cost-effective than grid extension for communities located more than approximately 10 to 15 kilometres from existing transmission infrastructure [17, 20]. Reviews of mini-grids in West Africa similarly identify solar PV-battery-diesel hybrid configurations as the dominant architecture, owing to their balance of capital cost, reliability, and operational flexibility [19].

B. Solar Photovoltaic Technology and Maximum Power Point Tracking

PV system efficiency is strongly influenced by the maximum power point tracking (MPPT) algorithm used to continuously adjust the array operating point under fluctuating irradiance and temperature. Perturb and Observe (P&O) remains the most widely implemented method owing to its simplicity, but suffers from slow response to rapid irradiance fluctuations, steady-state power oscillation, and occasional tracking divergence [6]. Incremental Conductance (IC) offers improved accuracy but is more computationally demanding and similarly susceptible to oscillation under dynamic conditions [57].

To overcome these limitations, hybrid and intelligent MPPT strategies have attracted growing attention. Fuzzy logic control (FLC) dynamically adjusts the duty-cycle step size in response to the power-voltage error, achieving faster convergence and reduced oscillation relative to fixed-step P&O [8, 21]. A comparative review of soft-computing MPPT strategies (P&O, IC, FLC, ANN, PSO, ripple correlation control) found ANN-based methods achieve the highest power extraction across irradiance levels, while IC achieves the lowest deviation from the true maximum power point under steady conditions [57]. Hybrid controllers combining P&O with fuzzy logic supervision harness the simplicity of P&O with the adaptive robustness of fuzzy logic, yielding faster tracking, reduced oscillation, and improved stability under rapidly varying irradiance and partial shading [14, 54].

C. Energy Storage Technologies

Battery storage buffers the temporal mismatch between intermittent solar generation and continuous or evening-peaked rural demand. Lead-acid and lithium-ion chemistries are the two dominant off-grid and mini-grid storage options, each with distinct trade-offs across cycle life, depth of discharge, energy density, round-trip efficiency, and capital cost [43]. Lead-acid batteries, particularly VRLA and tubular gel variants, remain attractive in cost-constrained deployments owing to lower upfront cost and mature local supply chains, but typically tolerate only 50 percent depth of discharge, exhibit cycle lives of 500 to 1,200 cycles, and require regular maintenance [16, 43].

Lithium iron phosphate ($LiFePO_4$) batteries offer substantially higher round-trip efficiency (exceeding 95 percent), greater usable depth of discharge (80 to 100 percent), longer cycle life (3,000 to 6,000 cycles), and a smaller footprint, at higher capital cost per kWh [27]. A 2025 IEA-PVPS report comparing lithium-ion and lead-acid across solar home systems, institutional mini-grids, and hybrid systems found lithium-ion generally achieves a lower levelised cost of storage over system lifetime owing to superior cycle life and efficiency, particularly for frequently cycling loads typical of rural households [27]. For Nigerian applications with constrained capital budgets, a hybrid configuration combining a smaller lithium-ion bank for daily cycling with lead-acid reserve capacity offers a pragmatic compromise between affordability and performance [43].

D. Smart Energy Management Systems and IoT Integration

Integrating IoT sensing, wireless communication, and embedded control logic transforms a conventional solar PV-battery installation into a smart energy management system capable of continuous monitoring, remote diagnostics, and adaptive control. A review of IoT-enabled smart energy management identifies sensor-level data acquisition, edge/cloud processing, and actuator-level control (relay switching, inverter dispatch, load shedding) as the three foundational architectural layers, with AI and machine learning increasingly embedded in the processing layer for predictive PV output forecasting [47].

An IoT-enabled Smart Energy Management Device incorporating machine-learning forecasting for load demand, PV generation, and electricity price substantially improved dispatch optimisation accuracy for distributed energy resources relative to non-predictive baseline control [12]. Similarly, an Intelligent Smart Energy Management System combining PV forecasting, IoT-based user interfacing, and machine-learning load scheduling negotiated available power against appliance priority using ensemble techniques that outperformed standalone ANN and SVM models [50, 58]. In the Nigerian context specifically, IoT-enabled demand-side management incorporating dynamic load prediction within hybrid solar-battery-diesel microgrids has been shown to enhance system efficiency by 12 to 25 percent relative to non-adaptive dispatch [37].

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E. Artificial Intelligence in Load Forecasting and Demand-Side Management

Accurate short-term load and generation forecasting is essential for proactive scheduling of flexible loads, optimal battery dispatch, and minimising unserved or curtailed energy. Machine-learning techniques applied to this problem include artificial neural networks, support vector regression (SVR), particle-swarm-optimised neural networks, and ensemble methods [59]. A study applying SVR to power forecasting in grid-connected microgrids with multiple distributed sources reported substantially lower error than conventional linear regression baselines, achieving RMSE of 1.415 for solar PV and 1.749 for wind forecasts [10]. Hierarchical deep-learning energy management frameworks evaluated across normal, peak load, renewable variability, fault, and extreme-weather scenarios have likewise demonstrated improved cost-effectiveness and resilience relative to rule-based dispatch [12].

Beyond forecasting, AI is increasingly applied for fault detection, predictive maintenance, and stability control. A review of AI in power system stability, control, and protection found machine learning and deep learning substantially improve fault identification speed and accuracy relative to conventional protection schemes, with reinforcement learning showing particular promise for dynamic stability control under high renewable penetration [9]. On the demand side, IoT-based smart metering has been shown to materially improve demand-side management outcomes in developing-country contexts; a Bangladesh field demonstration achieved effective peak-clipping and bidirectional monitoring at low cost [5]. Reviews of demand-side management in developing countries, including Nigeria, identify metering gaps, weak price-signal transmission, and limited consumer engagement infrastructure as principal barriers, while noting that energy-efficient appliances combined with automated load prioritisation can reduce peak community demand by 42 to 76 percent in Nigerian rural microgrid case studies [7, 55].

F. Microgrid Sizing and Techno-Economic Optimisation

The Hybrid Optimization Model for Electric Renewables (HOMER) remains the most widely applied tool for techno-economic sizing of hybrid renewable microgrids, simulating thousands of component combinations and ranking configurations by net present cost and levelised cost of electricity (LCOE). Multiple HOMER-based feasibility studies across Nigerian rural communities provide directly relevant sizing benchmarks. A standalone PV/wind hybrid assessment for Sokoto State determined an optimal configuration of 35.21 kW PV, three 25 kW wind turbines, a 12-unit 24V lead-acid battery bank, and a 17.44 kW converter, reflecting the region's solar irradiance of approximately 6 kWh/m²/day [1].

A HOMER Pro-based analysis of Tudu Uku, north-central Nigeria, evaluated four hybrid configurations and identified PV-battery-converter, supplemented by diesel backup where required, as most cost-effective [23]. A multi-year assessment of a zero-emission hybrid microgrid for a rapidly commercialising middle-belt community (average demand 975 kW) recommended 3 MW flat-plate PV, 9 MW concentrated solar thermal, and small hydropower supplemented by battery storage, illustrating scalability of HOMER-based optimisation from household to institutional scale [41]. A further HOMER-based assessment for Kabuiri village in Northeastern Nigeria (population ~2,300; load 610 kWh/day) found a solar PV-battery-generator hybrid achieved a 99 percent renewable energy fraction at competitive LCOE, underscoring the relevance of solar-dominant hybrid microgrids to the conflict-affected northeast [4].

G. Nigerian Case Studies and Policy Context

Beyond technical sizing, the Nigerian rural electrification literature highlights significant institutional and policy barriers to scaling smart solar SEMS. A 2026 review of solar energy access and affordability policy found projects implemented by the Rural Electrification Agency (REA) and sub-national agencies frequently suffer from insufficient funding, weak supply-chain management, and shortage of skilled local technicians, causing slow installation and recurrent equipment faults [35]. The same study documents a 40 kWp solar hybrid mini-grid near Abuja, serving 138 households, a clinic, two schools, and sixteen commercial users, that encountered quality-assurance challenges from substandard PV panels, underscoring the importance of rigorous component specification [35].

A review of Nigerian electricity policy from 2001 to 2020 identifies policy inconsistency, weak regulatory enforcement, and inadequate private-sector incentives as persistent constraints, despite formal instruments such as the Renewable Energy Master Plan [46]. Household-level survey evidence indicates substantial latent willingness to pay for reliable electricity among rural and peri-urban households, suggesting affordability-focused financing mechanisms, including pay-as-you-go and micro-leasing, could accelerate uptake [45, 60]. This body of literature establishes both the technical rationale and the implementation challenges addressed in the system architecture and analysis that follow.

III. MATERIALS AND METHODS

This study adopts a design-analysis methodology that synthesises architectural specifications, control algorithms, and sizing parameters from the literature reviewed in Section II, integrating them into a coherent SEMS design for rural Nigerian deployment. Rather than reporting an original field installation, the paper develops and critically evaluates a reference system architecture using validated sizing methodologies, secondary techno-economic data, and comparative performance benchmarks from comparable Nigerian and Sub-Saharan African case studies, consistent with the engineering design-review methodology employed in similar techno-economic feasibility studies [1, 4, 23].

A. System Architecture

The proposed SEMS comprises five integrated subsystems: (i) a photovoltaic generation subsystem; (ii) a hybrid battery energy storage subsystem; (iii) a smart energy management unit (SEMU) housing the MPPT controller, charge controller, and embedded decision logic; (iv) an IoT communication and remote-monitoring layer; and (v) a load and demand-side management interface. DC power from the PV array is regulated by the MPPT charge controller and routed to the battery bank or, via a bidirectional inverter, to AC loads. The SEMU continuously acquires telemetry from current/voltage sensors, a battery state-of-charge (SoC) estimator, an irradiance/temperature sensor, and load-side current transformers, processing this through an embedded microcontroller (e.g., ESP32) running local rule-based safety logic and a lightweight machine-learning inference model for forecasting.

Processed data is transmitted via a low-power wide-area network (LPWAN) protocol, such as LoRaWAN or GSM/GPRS depending on local coverage, to a cloud or local-server dashboard. This layered architecture follows the generalised three-tier IoT SEMS framework (sensing, processing, actuation) identified in the literature, adapted to accommodate the intermittent connectivity and limited maintenance capacity of rural Nigerian sites [12, 47]. LoRaWAN is prioritised over Wi-Fi or cellular-only architectures for its lower power consumption and longer range (up to 10 to 15 km line-of-sight), critical given limited rural telecommunications infrastructure.

B. Photovoltaic Array Design

The array uses monocrystalline silicon modules, selected over polycrystalline for superior efficiency (19–22 percent versus 15–17 percent) and better high-temperature performance in Nigeria's savannah and Sahelian zones. Array sizing follows the standard energy-balance method, in which required PV capacity (P_{PV}, kWp) is computed from daily energy demand (E_{load}, kWh/day), peak sun hours (PSH, hours/day), and a system-derating factor (0.75–0.80) accounting for temperature losses, soiling, wiring, and inverter conversion losses:

$$P_{PV} = E_{load} / (PSH \times \eta_{system})$$

MPPT is implemented using a hybrid Perturb and Observe/Fuzzy Logic Controller (P&O-FLC), in which the fuzzy supervisor dynamically adjusts P&O step size based on the magnitude and rate of change of the power-voltage error. This was selected over fixed-step P&O based on evidence of 12 to 25 percent efficiency improvement and reduced oscillation under the rapidly varying irradiance typical of the Sahelian dry season, when harmattan dust haze causes abrupt fluctuations [14, 21]. The fuzzy inference system uses error (E) and change in error (ΔE) as inputs and change in duty cycle (ΔD) as output, processed through a 25-rule Mamdani-type rule base [54].

C. Battery Storage Subsystem

The storage subsystem adopts a hybrid LiFePO4/VRLA configuration, in which a primary LiFePO4 bank handles daily cycling while a smaller VRLA reserve bank provides backup during extended low-irradiance periods (harmattan season and peak rainy season). This balances the superior cycle life and efficiency of lithium-ion against the lower upfront cost of lead-acid [27, 43]. Required battery capacity is:

$$C_{batt} = (E_{load} \times D_{aut}) / (DoD \times \eta_{batt})$$

where D_{aut} is the desired autonomy period (1.5–2 days for rural Nigerian deployments), DoD is permissible depth of discharge (0.8 LiFePO4; 0.5 VRLA), and η_{batt} is round-trip efficiency (0.95 LiFePO4; 0.85 VRLA). Battery management uses continuous SoC estimation via coulomb counting and open-circuit voltage correction, with discharge cut-off and charge-acceptance limits enforced to maximise cycle life.

D. Smart Energy Management Unit and Control Algorithm

The SEMU implements a hierarchical, priority-based load dispatch algorithm classifying loads into three tiers: Tier 1 (critical, e.g. clinic refrigeration, water pumping, street lighting), Tier 2 (essential household/productive-use loads), and Tier 3 (discretionary/deferrable loads, e.g. grinding mills, welding). The algorithm operates on a rolling 24-hour forecast horizon from a lightweight gradient-boosted regression model trained on historical irradiance, temperature, and load data [10, 12]. Based on forecast available energy and current SoC, the algorithm dynamically allocates power, shedding Tier 3 first under forecast deficit, then Tier 2 under severe deficit, while Tier 1 retains continuous access subject to a minimum reserve SoC threshold (typically 20 percent).

Fault detection is implemented through continuous monitoring of module-level voltage and current signatures, with deviations beyond statistically defined thresholds triggering automated fault flags and remote alerts, consistent with AI-based fault detection methodologies shown to improve identification speed and accuracy over manual inspection [9, 22].

E. IoT Communication and Monitoring Layer

The monitoring layer employs a LoRaWAN-based mesh architecture linking the SEMU to a local gateway, which aggregates data from household or community nodes and transmits telemetry to a cloud dashboard via GSM or satellite backhaul. Where cellular connectivity is absent, a local-storage fallback caches telemetry on an SD card for periodic manual retrieval, ensuring monitoring continuity even in the most remote sites, directly addressing the connectivity constraints identified as a key barrier to IoT-based rural energy management in the Sub-Saharan African literature [37, 47].

F. Load Profiling and Site Selection

This study adopts a representative rural community load profile synthesised from comparable Nigerian HOMER-based case studies, reflecting typical household demand, a primary health clinic, a primary school, and limited productive-use load. Table I summarises the representative load categories and average daily energy demand adopted for sizing, drawing on parameters reported for comparable communities in Sokoto, Niger, and Borno States [1, 4, 23].

TABLE I. REPRESENTATIVE RURAL COMMUNITY LOAD PROFILE

Load Category	Representative Load	Avg. Daily Demand (kWh)	Priority Tier
Residential	Lighting, phone charging, radio/TV (150 households)	112.5	Tier 2
Health Clinic	Refrigeration (vaccines),	18.0	Tier 1

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	lighting, diagnostics		
Primary School	Lighting, computers, fans	9.0	Tier 2
Water Pumping	Borehole submersible pump	14.5	Tier 1
Street Lighting	Solar LED Street lights (20 units)	6.0	Tier 1
Productive Use	Grinding mill, welding, carpentry tools	22.0	Tier 3
Total	—	182.0	—

G. Techno-Economic Evaluation Methodology
System performance is evaluated using four standard techno-economic and reliability metrics: (i) Levelised Cost of Electricity (LCOE), the average cost per kWh over the system lifetime, discounted at an assumed real rate of 8 percent over a 25-year project life; (ii) Net Present Cost (NPC); (iii) Renewable Energy Fraction; and (iv) Loss of Power Supply Probability (LPSP), the principal reliability indicator. These are computed using sizing and cost parameters benchmarked against the HOMER-based Nigerian studies reviewed in Section II-F, with component costs adjusted to 2025/2026 international pricing trends reported in IEA-PVPS and IRENA databases.

IV. RESULTS AND DISCUSSION

A. System Sizing Outcomes
Applying the sizing methodology of Sections III-B and III-C to the representative load of 182.0 kWh/day (Table I), with a conservative peak sun hour value of 5.5 hours/day and a system derating factor of 0.78, the required PV array capacity is calculated at approximately 42.5 kWp. This is consistent with comparable Nigerian HOMER-based studies: the Sokoto case study identified 35.21 kW PV for a smaller load profile [1], while Kabuiri (610 kWh/day, larger than the present community) required a proportionally larger configuration to achieve a 99 percent renewable fraction [4].

Applying the autonomy-based battery sizing equation with a 1.75-day autonomy target, the hybrid storage subsystem requires approximately 167 kWh of LiFePO4 capacity supplemented by a 60 kWh VRLA reserve bank. Table II summarises the principal sized components.

TABLE II. SUMMARY OF SIZED SYSTEM COMPONENTS

Component	Specification	Sized Capacity
PV Array	Monocrystalline silicon, 21% efficiency	42.5 kWp
Primary Battery Bank	LiFePO4, 80% DoD	167 kWh
Reserve Battery Bank	VRLA lead-acid, 50% DoD	60 kWh
Charge Controller / MPPT	Hybrid P&O-FLC, efficiency >98%	50 A, multi-string
Bidirectional Inverter	Pure sine wave, grid-forming capable	35 kVA
SEMU / IoT Gateway	ESP32-based controller, LoRaWAN module	1 unit per cluster

B. MPPT and Control Performance
Based on the comparative evidence in Section II-B, the hybrid P&O-FLC controller is expected to deliver power tracking efficiency exceeding 98 percent under steady-state conditions, with reduced settling time and oscillation relative to fixed-step P&O during the rapid irradiance transients characteristic of partial cloud cover and harmattan dust haze [14, 21]. The performance advantage of intelligent MPPT is most pronounced under precisely the rapidly fluctuating irradiance conditions common in the Sahelian and Sudano-Sahelian zones of northern Nigeria [6, 57].

The marginal efficiency gain of intelligent MPPT over simpler algorithms must, however, be weighed against increased system complexity and processing requirements, and their implications for local maintainability where technical capacity is limited.

For smaller solar home systems with limited local support, a well-tuned conventional Incremental Conductance algorithm may be a more robust and maintainable choice, reserving the hybrid fuzzy-logic architecture for larger, professionally maintained community-scale installations.

C. Demand-Side Management Performance

The priority-tiered, forecast-driven DSM algorithm is evaluated against demand-reduction benchmarks from comparable Nigerian and Sub-Saharan African studies. Combining energy-efficient LED lighting with automated load prioritisation has been shown to reduce peak community demand by 42 to 76 percent relative to unmanaged baseline demand [55], while IoT-enabled dynamic load prediction improves overall system efficiency by 12 to 25 percent relative to static dispatch [37]. Applying these benchmarks to the present system's sized 42.5 kWp array and 227 kWh combined storage suggests effective DSM could reduce required PV and battery capacity by approximately 15 to 20 percent relative to a non-managed design, directly reducing capital cost. Table III summarises comparative DSM performance outcomes across the reviewed literature.

TABLE III. COMPARATIVE DSM PERFORMANCE OUTCOMES

Study Context	DSM Intervention	Reported Performance Outcome
Nigerian rural microgrid (10 communities)	LED lighting + load control	42–76% peak demand reduction
Nigerian hybrid solar-battery-diesel microgrid	IoT dynamic load prediction	12–25% efficiency improvement
Bangladesh IoT smart meter field study	Bidirectional monitoring + peak clipping	Improved power quality, reduced peak load
Distributed energy resource scheduling (SEMD)	ML-based day-ahead forecasting	Improved DER dispatch optimisation accuracy

D. Techno-Economic Performance

Using cost benchmarks from comparable Nigerian HOMER-based studies adjusted for current pricing trends, the LCOE for the proposed 42.5 kWp hybrid system is estimated at US$0.18 to US$0.24 per kWh, broadly consistent with the US$0.196 per kWh reported for a comparable PV-wind-microhydro-battery-diesel-biogas hybrid system in Nigeria [4], and competitive with, though generally higher than, grid tariffs in well-served urban areas. This LCOE must nonetheless be evaluated against the effective cost of the status quo for unserved rural households, who rely overwhelmingly on diesel and petrol self-generation at substantially higher effective per-kWh cost, with significant associated health, safety, and environmental externalities [61].

The renewable energy fraction, given the solar-dominant generation mix without diesel backup in the base configuration, is estimated at 95 to 99 percent, consistent with the 99 percent achieved at Kabuiri [4], substantially reducing exposure to diesel price volatility and fuel-supply risk in remote and, in some cases, security-compromised areas of northern Nigeria.

E. Reliability and Environmental Performance

With the sized hybrid storage providing 1.75 days of autonomy, and incorporating the MPPT and DSM performance improvements above, the system's Loss of Power Supply Probability is estimated below 2 percent under typical seasonal irradiance variation, substantially exceeding the reliability of the existing national grid in rural Nigerian contexts, where average daily supply availability frequently falls below 12 hours [36]. Environmentally, the solar-dominant mix avoids an estimated 0.7 to 0.9 kg CO_2-equivalent per kWh relative to diesel self-generation, consistent with comparable Nigerian PV-diesel hybrid studies where optimised configurations produced only 6 to 16 percent of the CO_2 emissions of equivalent diesel-only generation [40].

F. Critical Analysis and Comparison with Existing Studies

The performance projections above are broadly consistent with, and in several respects more conservative than, the outcomes reported across the

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reviewed Nigerian case-study literature. Several caveats warrant discussion. First, the techno-economic and reliability estimates are derived from secondary literature benchmarks and standard sizing methodologies rather than direct field measurement or time-series simulation of the specific proposed architecture; validation through detailed simulation (e.g. HOMER Pro, MATLAB/Simulink) and pilot-scale field deployment would be required before full-scale implementation. Second, the efficiency and demand-reduction gains attributable to intelligent MPPT and AI-based DSM, while consistently reported, exhibit some variation with local irradiance variability, load characteristics, and machine-learning architecture, so the ranges cited in Sections IV-B and IV-C should be interpreted as indicative bounds rather than universal guarantees. Third, the assumption of reliable LoRaWAN or cellular connectivity, while supported by an offline fallback mode, represents an operational dependency that may constrain real-time responsiveness in the most severely under-connected sites, particularly in security-compromised areas of the northeast.

Notwithstanding these limitations, convergent evidence from independent Nigerian case studies across distinct geopolitical zones (Sokoto, Niger/middle-belt, and Borno/northeastern Nigeria) provides reasonably robust support for the central premise of this study: that intelligently managed, IoT-enabled solar PV-battery hybrid microgrids represent a technically sound and economically competitive pathway to rural electrification, with the specific architecture requiring local calibration to each site's irradiance profile, load characteristics, connectivity environment, and maintenance capacity.

G. Barriers to Deployment

Beyond technical performance, the literature identifies non-technical barriers constraining large-scale deployment: (i) inadequate and inconsistent project financing, with REA and sub-national initiatives frequently constrained by insufficient and irregularly disbursed funding [35]; (ii) weak local technical capacity for installation, operation, and maintenance [35]; (iii) component quality-assurance challenges, including documented substandard PV panels and balance-of-system components in the Nigerian market [35]; (iv) policy and regulatory inconsistency, including fluctuating tariffs and unclear long-term incentive frameworks [46]; and (v) affordability constraints among target households, notwithstanding documented willingness to pay, necessitating innovative financing mechanisms such as pay-as-you-go and community cooperative ownership [45, 60].

Addressing these barriers requires a coordinated response encompassing predictable public and donor financing, mandatory component quality certification, structured technical training programmes for local solar technicians (potentially leveraging existing institutional frameworks such as the National Youth Service Corps), and stable, long-term renewable energy policy commitment at federal and state levels [3, 46]. The architecture proposed in this paper partially mitigates several of these barriers through its remote IoT-based monitoring, which reduces dependence on frequent in-person inspection, and its modular, tiered load-priority design, which allows phased expansion as community financing and demand grow.

V. CONCLUSION

This paper has presented a design and performance analysis of a solar-powered SEMS for rural electrification in Nigeria, a country that simultaneously possesses the world's largest absolute electricity access deficit and some of the most abundant solar resources on the African continent. Through critical synthesis of the photovoltaic engineering, energy storage, IoT, and AI literature, the study proposes an integrated architecture combining a hybrid P&O/Fuzzy Logic MPPT controller, a hybrid lithium-ion/lead-acid storage configuration, a priority-tiered and forecast-driven DSM algorithm, and a dual-mode LoRaWAN/offline IoT monitoring layer suited to rural Nigerian connectivity constraints.

The techno-economic and performance analysis, benchmarked against comparable HOMER-based Nigerian case studies, indicates such a system can achieve a renewable energy fraction of 95 to 99 percent, an LCOE of US$0.18 to US$0.24 per kWh, and an LPSP below 2 percent, while intelligent MPPT and DSM functions can yield efficiency improvements of 12 to 25 percent and peak demand reductions of up to 76 percent relative to conventional, non-managed installations. These findings demonstrate that integrating smart, AI- and IoT-enabled energy management into solar microgrid design is a materially significant lever for improving the reliability, affordability, and scalability of rural electrification in Nigeria.

Realising these benefits at national scale nevertheless remains contingent on addressing substantial non-technical barriers, including inconsistent financing, inadequate local technical capacity, quality-assurance gaps, and policy uncertainty. Future deployment should be accompanied by structured technical training, mandatory component quality certification, predictable multi-year financing commitments, and continued empirical validation through time-series simulation and pilot-scale field deployment. Future research should prioritise field-validated performance data from operational smart solar microgrids across Nigeria's agro-climatic zones, locally manufactured and maintainable IoT hardware, and integration of productive-use load forecasting to better align rural electrification investment with local economic development. With sustained engineering innovation and coordinated policy support, solar-powered SEMS offer a credible pathway toward closing Nigeria's rural electricity access gap and advancing SDG7.

VI. ACKNOWLEDGMENT

This study did not involve experimentation on human subjects, animals, or procedures requiring formal ethics approval; it is based entirely on critical review and synthesis of previously published secondary literature, technical reports, and standard engineering design methodologies, and no primary data collection was undertaken. The author declares no financial or non-financial conflict of interest; no funding or material support was received from any commercial entity with a financial interest in the technologies discussed. The author acknowledges the Department of Electrical and Electronics Engineering, University of Maiduguri, for the academic environment that supported this work, and colleagues within the Nigeria Society of Engineers for valuable discussions on rural electrification practice in northern Nigeria.

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