electronics

Review

Intelligent Hybrid Solar–Wind Off-Grid (Standalone) Electric Vehicle Charging Stations for Remote Areas and Developing Countries: A Comprehensive Review

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Abstract

Off-grid electric vehicle (EV) charging infrastructure powered by hybrid solar–wind systems address critical adoption barriers in developing countries, where grid unreliability and sparse charging networks constrain transportation electrification. Despite growing research interest, no comprehensive review has systematically synthesized the interplay between hybrid renewable architectures, intelligent energy management strategies, and techno-economic viability specifically for off-grid EV charging in resource-constrained settings. This systematic review applies the PRISMA methodology to analyze 94 peer-reviewed publications (2013–2026), examining system architectures, intelligent control strategies, power electronics, battery storage, and deployment frameworks for standalone hybrid solar–wind EV charging stations. Key findings indicate that hybrid solar–wind configurations achieve 30–50% reductions in battery storage requirements and 15–25% lower levelized cost of energy (LCOE) (USD 0.08–0.15/kWh) compared with single-source systems, driven by diurnal and seasonal resource complementarity. Among intelligent control methods, the two-stage distributionally robust optimization (TSDRO) framework emerges as the most promising for data-scarce environments, outperforming conventional deterministic and stochastic approaches by 10–20% in managing renewable intermittency without requiring precise probability distributions. Wide-bandgap power semiconductors (SiC, GaN) enable 96–98% conversion efficiency, while lithium iron phosphate batteries provide 3000–5000 cycle lifetimes suited to tropical operating conditions. Critical gaps remain with field validation still predominantly simulation based, long-term operational data exceeding 24 months on equipment degradation and climate resilience are scarce, and scalable financing models for developing country contexts require further development. Nigeria is presented as an exemplar deployment context, with transferable insights for sub-Saharan Africa, South Asia, and Southeast Asia.

Keywords: electric vehicle charging; hybrid solar–wind systems; off-grid infrastructure; intelligent energy management; distributionally robust optimization; battery storage; developing regions; levelized cost of energy

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1. Introduction

The transportation sector accounts for approximately 23–25% of global energy-related CO_2 emissions, with road vehicles responsible for over 70% of this share [1,2]. Electric vehicles (EVs) have emerged as a key decarbonization pathway, with global sales reaching

17 million units in 2024 and increasing 35% in the first quarter of 2025 compared with the same period in 2024 [3]. However, widespread EV adoption faces significant barriers in developing countries and remote areas, where inadequate charging infrastructure and unreliable electricity supply create substantial obstacles [4,5].

In this review, "remote areas" are defined as geographic regions characterized by five key attributes: (i) absence of or limited access to centralized electricity grid infrastructure, with grid distance exceeding 10 km or grid reliability below 50%; (ii) weak or non-existent transport and logistics infrastructure, resulting in supply chain lead times exceeding 7 days for standard equipment; (iii) low population density, typically below 150 persons/km^2; (iv) limited availability of trained technical personnel for system installation, operation, and maintenance; and (v) constrained access to formal financial services and conventional financing mechanisms. This definition is consistent with the criteria used by the International Energy Agency, the World Bank's Multi-Tier Framework for energy access, and the African Development Bank's rural electrification classifications. "Developing countries" are classified following the United Nations M49 Standard and the World Bank income classification (low-income and lower-middle-income economies with GNI per capita below USD 4466 in 2024), consistent with the UNDP Human Development Index threshold of HDI < 0.700.

Conventional EV charging infrastructure relies on grid connectivity, which is problematic in developing countries where approximately 675 million people lack electricity access entirely and an additional 2.3 billion experience unreliable supply with frequent outages lasting hours or days [4,5]. Sub-Saharan Africa has fewer than 500 public charging points serving 1.4 billion people, while India requires an estimated 400,000 charging stations by 2030 to support projected growth but currently has fewer than 10,000 [5,6]. This infrastructure gap constrains EV adoption and perpetuates fossil fuel dependency, necessitating alternative solutions independent of centralized grid infrastructure.

Among renewable energy sources, solar photovoltaic (PV) and wind energy are the most promising for off-grid applications due to declining costs, technological maturity, and widespread availability [7–9]. Solar PV module prices declined from USD 1.50/W in 2010 to USD 0.20/W in 2024, while lithium-ion battery pack costs fell from USD 1100/kWh to below USD 130/kWh over the same period [3,8]. However, both sources exhibit inherent intermittency—solar energy is unavailable at night and varies with cloud cover, while wind generation fluctuates with weather patterns. Hybrid solar–wind systems leverage the complementary nature of these resources, with wind speeds typically increasing during evening and nighttime hours when solar generation ceases [7,9,10]. Properly designed hybrid systems achieve capacity factors 20–40% higher than single-source systems while reducing battery storage requirements by up to 50% [7,9,10].

Recent advances in intelligent energy management have introduced adaptive control strategies that optimize power coordination among multiple renewable sources, predict generation and demand patterns using machine learning, and dynamically adjust operation in response to real-time conditions [11–16]. Advanced optimization frameworks, including two-stage distributionally robust optimization (TSDRO), enable effective decision-making under extreme uncertainties while accommodating data scarcity through techniques such as the Imprecise Dirichlet Model [17–20]. These approaches show promise for resource-constrained developing country contexts where robustness and minimal maintenance requirements are paramount.

Despite growing interest, the literature exhibits significant gaps. First, no comprehensive review has specifically addressed the integration of hybrid solar–wind systems with intelligent adaptive energy management for off-grid EV charging in developing country contexts characterized by limited technical expertise, harsh environmental conditions, and weak regulatory frameworks [5,21]. Second, the integration of advanced control strategies with hybrid systems specifically for off-grid EV charging remains underexplored, with most research treating these topics separately [15,21]. Third, existing studies overwhelmingly rely on simulation with limited real-world validation beyond 12–24 months [5,21]. Fourth, most sizing optimization studies employ single-objective formulations prioritizing cost minimization, lacking holistic frameworks integrating reliability, environmental impacts, and social objectives [9,22]. Finally, technical feasibility analyses dominate while business models, financing mechanisms, and policy incentives necessary for large-scale deployment receive inadequate attention [5,23].

1.1. Research Questions

To address these gaps systematically, this review is guided by the following research questions:

RQ1: What hybrid solar–wind system architectures, power electronic configurations, and battery storage technologies are most suitable for off-grid EV charging stations in developing countries, and what quantitative performance advantages does hybridization offer over single-source alternatives?

RQ2: How do intelligent energy management strategies, including rule-based, optimization-based, AI/ML-based, and distributionally robust optimization approaches compare in their ability to manage the dual uncertainties of renewable intermittency and EV charging demand in off-grid contexts, and what are their respective limitations under data scarcity?

RQ3: Can distributionally robust optimization frameworks, specifically two-stage DRO with Imprecise Dirichlet Models (TSDRO-IDM), effectively address the combined challenges of extreme uncertainty and limited historical data that characterize off-grid hybrid renewable EV charging in developing regions?

RQ4: What are the techno-economic conditions—including levelized costs, financing mechanisms, implementation challenges, and operational data gaps—under which off-grid hybrid solar–wind EV charging stations become commercially viable in developing countries, and what evidence exists from real-world deployments?

By addressing these questions, this review aims to provide a holistic assessment of the current state of the art, identify critical research gaps, and chart a research roadmap for making intelligent hybrid solar–wind off-grid EV charging a practical reality in sub-Saharan Africa, South Asia, and Southeast Asia.

1.2. Rationale and Significance

Several converging factors make this study both timely and necessary. First, the scale of the problem is immense and growing. Approximately 675 million people worldwide lack electricity access, the vast majority in sub-Saharan Africa and South Asia [4,5], while road transport emissions in developing countries are rising sharply as vehicle ownership expands—projected to double by 2050 without intervention [1,2]. These regions face a dual imperative: decarbonizing transport and expanding energy access simultaneously. Off-grid hybrid renewable EV charging offers the rare opportunity to address both imperatives through a single infrastructure investment, yet no comprehensive review has synthesized the multidisciplinary knowledge required to make this a reality.

Second, existing reviews treat the constituent technologies in isolation. Reviews of hybrid renewable energy systems focus on sizing and optimization without addressing EV charging's unique demand profiles [7,9]. Reviews of EV charging infrastructure assume grid connectivity that does not exist in the target regions [21,24]. Reviews of intelligent energy management evaluate algorithms in idealized simulation environments disconnected from the harsh realities—extreme heat, dust, flooding, supply chain constraints—that determine success or failure in the field [15,17]. This fragmentation leaves practitioners, policymakers, and investors without an integrated evidence base for decision-making. By synthesizing across system architectures, power electronics, storage, intelligent control, AI/ML, and techno-economics within a unified developing-country framework, this review fills a critical gap that none of these domain-specific reviews addresses individually.

Third, the technological window of opportunity is narrowing. Solar PV costs have fallen 90% since 2010, lithium-ion batteries 88%, and wide-bandgap semiconductors are reaching cost-performance inflection points [3,8,25]. Developing countries that act now can leapfrog directly to clean electric mobility—much as mobile telephony bypassed landlines—while those that delay risk locking in fossil-fuel vehicle infrastructure for decades [5,23]. This review provides the technical and economic evidence base needed to inform these time-sensitive decisions.

Fourth, the methodological contribution is significant. Conventional optimization approaches for hybrid system sizing and operation either assume probability distributions that do not exist in data-scarce regions (stochastic programming) or produce overly conservative solutions that inflate costs by 18–25% (robust optimization) [17–20,26]. By identifying and evaluating the TSDRO framework with Imprecise Dirichlet Models, which explicitly address data scarcity and extreme uncertainty, this review introduces a methodological paradigm shift specifically tailored to the constraints of developing country deployments. This framework has not previously been examined in the context of off-grid EV charging.

Fifth, the practical impact potential is substantial. Nigeria alone has over 220 million people, 12 million registered vehicles, and some of the world's highest solar irradiation (5–6 kWh/m^2/day) alongside chronic grid deficiency (4000 MW available versus 20,000 MW demand) [22,27–29]. The findings of this review are directly transferable to similar contexts across 48 sub-Saharan African countries, the Indian subcontinent, Southeast Asia, and small island developing states—collectively representing over 3 billion people and the fastest-growing vehicle markets globally. By documenting real-world deployment experience including implementation challenges, operational data gaps, and lessons learned, this review provides actionable guidance for the next generation of projects, potentially preventing the repetition of costly mistakes and accelerating the timeline from pilot to scale.

Collectively, this review contributes to the field in five ways: (i) providing the first integrated, multidisciplinary assessment of hybrid solar–wind off-grid EV charging specifically for developing country contexts; (ii) establishing a taxonomy and comparative evaluation of intelligent energy management strategies for this application; (iii) introducing distributionally robust optimization under data scarcity as a promising methodological framework for off-grid renewable system operation; (iv) synthesizing scarce real-world deployment data to bridge the gap between simulation studies and field realities; and (v) charting an evidence-based research roadmap that prioritizes the most impactful directions for future investigation.

1.3. Review Methodology

This systematic review follows PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [30]. The literature was identified through structured searches of Scopus, Web of Science, and IEEE Xplore databases using Boolean combinations of key terms: ("electric vehicle" OR "EV") AND ("solar" OR "photovoltaic") AND ("wind") AND ("charging" OR "off-grid" OR "standalone" OR "microgrid") AND ("hybrid" OR "renewable"). The search was restricted to English-language peer-reviewed publications from January 2013 to March 2026. Regions were classified as "developing countries" based on three internationally standardized criteria: the United Nations M49 Standard country classification, the World Bank income grouping (low-income and lower-middle-income economies, GNI per capita below USD 4466), and the UNDP Human Development Index (HDI < 0.700). These criteria were selected because they are widely used in energy access literature, are reproducible, and correlate directly with the infrastructure deficits that motivate this review's focus on off-grid solutions. Initial searches yielded 848 records. After removing 312 duplicates, 536 records were screened by title and abstract, yielding 249 articles for full-text assessment. Of these, 156 were excluded for insufficient relevance (e.g., grid-connected-only systems, non-EV applications, editorial content, or studies lacking quantitative performance data), resulting in 94 publications included in the final synthesis. Figure 1 presents the PRISMA flow diagram detailing this selection process.

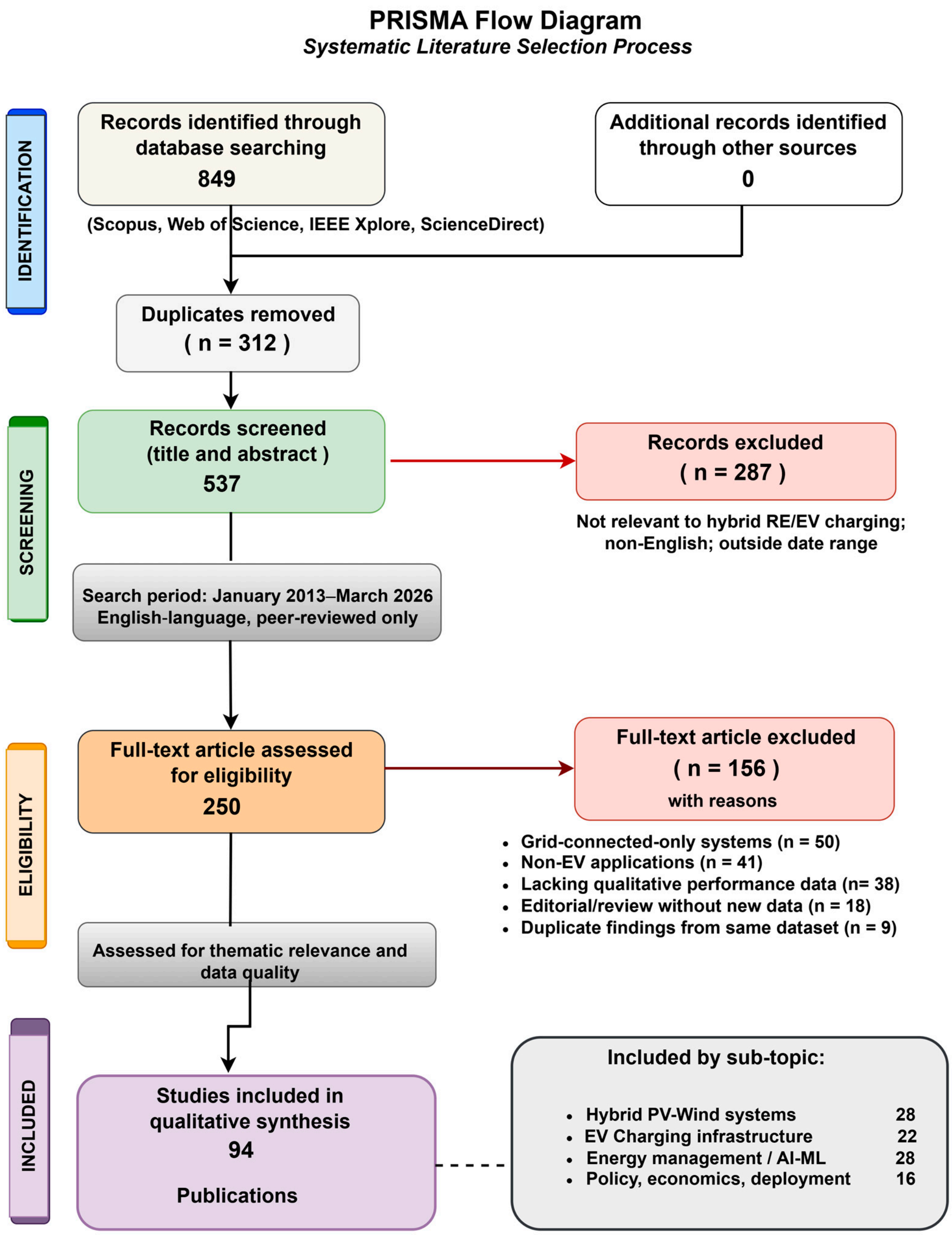

Figure 1. PRISMA flow diagram for the systematic literature selection process.

The remainder of this paper is organized as follows. Section 2 examines EV charging challenges in developing countries with Nigeria as a case study (addressing RQ1 and RQ4 context). Section 3 analyses hybrid solar–wind system architectures and resource complementarity (RQ1). Section 4 reviews enabling technologies in power electronics and battery storage (RQ1). Section 5 evaluates intelligent energy management strategies including the TSDRO framework (RQ2 and RQ3). Section 6 surveys artificial intelligence and machine learning applications (RQ2). Section 7 assesses techno-economic viability and deployment experience (RQ4). Section 8 identifies research gaps and future directions. Section 9 presents conclusions.

2. Charging EV Infrastructure in Developing Countries

While the global EV market has experienced exponential growth—with the global stock projected to grow from approximately 45 million in 2023 to 250 million by 2030 [31,32]—this expansion remains highly concentrated in China (60% of 2024 registrations), Europe (25%), and North America (10%) [6,33]. Developing countries face fundamentally different conditions that require distinct infrastructure solutions. This section examines the unique challenges and opportunities, followed by a case study of Nigeria as a representative deployment context.

2.1. Challenges and Opportunities

Developing countries face interconnected barriers to EV adoption that differ fundamentally from developed market contexts [4,5,23]. As defined in Section 1, remote areas in these regions are characterized by grid inaccessibility, weak logistics infrastructure, low population density, limited technical capacity, and constrained access to financing—conditions that collectively preclude conventional grid-dependent charging solutions and necessitate the off-grid hybrid renewable approaches examined in this review. Table 1 summarizes these challenges alongside countervailing opportunities. The most acute challenge is unreliable grid infrastructure: sub-Saharan African countries experience thousands of hours of power outages annually, with grid reliability frequently below 50% [4,5]. Public charging infrastructure is virtually non-existent, with sub-Saharan Africa having fewer than one charging point per million people compared with approximately 5000 per million in Amsterdam—a disparity spanning three orders of magnitude [3,8]. Combined with high upfront EV costs (30–50% premium over combustion vehicles), limited consumer financing, per capita incomes of USD 1500–3000 in rural areas, scarce technical capacity for maintenance, and underdeveloped regulatory frameworks (fewer than 20% of developing countries have dedicated EV strategies), these barriers create an environment where conventional grid-dependent charging solutions are impractical [4–6,23].

Table 1. Public EV charging infrastructure disparity across regions [3,8].

Region/City	Population	Public Charging Points	Points per Million People
Sub-Saharan Africa	1.2 billion	<1000	<1
Amsterdam	900,000	4000–5000	4444–5556
Europe	450 million	675,000	1500
China	1.4 billion	1.6 million	1143
North America	370 million	270,000	730

However, these challenges are counterbalanced by significant opportunities. Many developing regions possess exceptional solar and wind resources—Africa receives 4–7 kWh/m^2/day solar irradiation across most regions, while coastal and highland areas have wind potential exceeding 7–8 m/s mean annual speeds [8]. Despite this abundance, installed renewable capacity represents less than 5% of technical potential [5,8]. Developing countries can potentially leapfrog fossil-fuel vehicle infrastructure, directly transitioning to electric mobility powered by distributed renewable energy, analogous to how mobile telecommunications bypassed landline infrastructure [5,23]. Off-grid renewable charging can simultaneously address transportation electrification and energy access, providing community electricity services beyond vehicle charging—including lighting, telecommunications, refrigeration, and productive uses—creating integrated energy hubs that accelerate rural development [5,9]. Electric two- and three-wheelers are already gaining traction in many developing markets due to lower costs and suitability for local transport needs, requiring less charging capacity and making off-grid solutions more feasible [3,6]. Finally, rapid cost reductions in solar PV (90% since 2010), wind turbines (60–70%), and battery storage (88%) are improving economic viability, particularly when compared with extending unreliable grid infrastructure to remote areas at costs of USD 150–300 per kWh of delivered capacity [5,7,8].

Figure 2 illustrates the interconnected structural barriers and enabling factors influencing the deployment of off-grid hybrid renewable EV charging systems in developing countries. Key challenges—including grid unreliability, infrastructure deficits, high capital costs, limited technical capacity, and policy gaps—are mapped against corresponding opportunities such as abundant renewable resources, leapfrogging potential, rural development co-benefits, emerging two- and three-wheeler markets, and declining technology costs. The directional linkages emphasize how strategic integration of hybrid renewable systems and intelligent energy management can transform systemic constraints into scalable and sustainable deployment pathways.

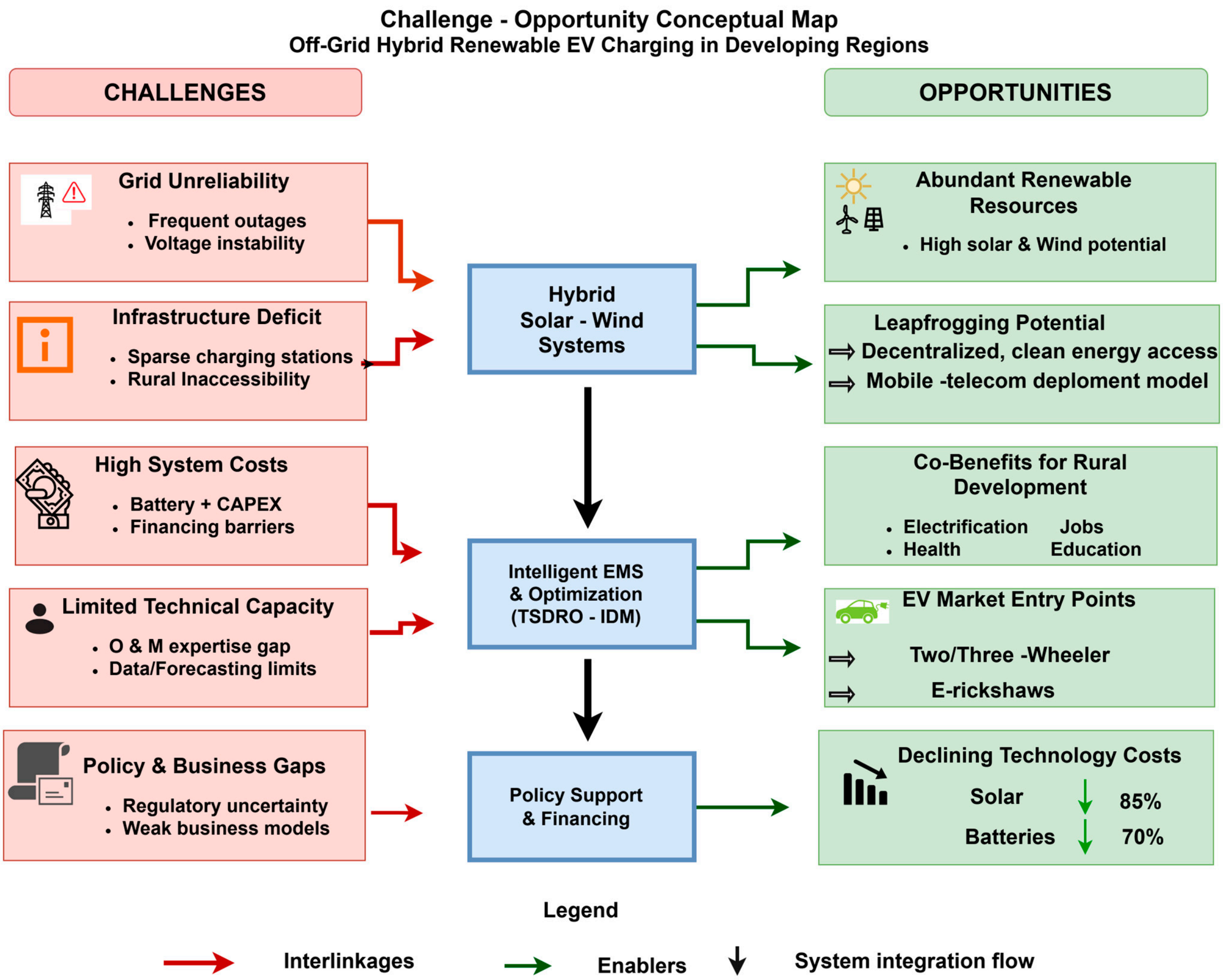

Figure 2. Challenge–Opportunity conceptual map for off-grid hybrid solar–wind EV charging in developing regions. Note 85% decrease in costs for solar and 70% decrease in costs for battery technologies.

For off-grid renewable systems in developing regions, Level 2 AC charging (3.7–22 kW) represents the optimal balance between charging speed, system cost, and generation capacity requirements, achieving 60–80% lower capital costs than Level 3 DC fast charging while providing acceptable 3–6 h charging times suitable for overnight and workplace scenarios [5,7,10,24]. This power level aligns well with hybrid solar–wind systems at distributed generation scales (10–25 kW PV arrays, 5–10 kW wind turbines), enabling cost-effective battery storage integration (20–50 kWh) for typical daily driving needs of 30–50 km prevalent in developing countries.

2.2. Nigeria as a Representative Case Study

Nigeria exemplifies the dynamics of developing country EV charging with clarity. As Africa's most populous nation (>220 million people) and largest economy (GDP USD 477 billion in 2022) [27], Nigeria represents a substantial market for sustainable transportation solutions with over 12 million registered vehicles and a growing middle class [22]. Yet the country faces one of the world's most severe energy access challenges: despite being Africa's largest oil producer, the national grid's available power often hovers around 4000 MW—far below the estimated demand of 20,000 MW—and grid-connected households receive, on average, just 6.6 h of electricity per day [28,29]. The rural electrification rate stands at approximately 39% compared with 78% in urban areas [28].

Nigeria possesses exceptional renewable resources. The country lies within a high-sunshine belt between latitudes 4° and 14° N, with solar irradiation of 5–6 kWh/m^2/day across most regions [22,34]. Wind speeds in northern regions range from 4.0 to 8.6 m/s, and coastal areas including Lagos and the Niger delta have significant wind potential [22,35]. The complementary nature of these resources—solar output strongest during daytime, wind often picking up at night and during different seasons—makes Nigeria particularly well suited for hybrid solar–wind systems [36,37]. The transportation sector accounts for approximately 22% of national emissions [38], with heavy reliance on imported refined petroleum products placing substantial pressure on foreign exchange reserves [39], while vehicle emissions in cities like Lagos exceed WHO permissible limits for $PM_{2.5}$ and carbon monoxide [40,41].

Policy frameworks including the National Renewable Energy and Energy Efficiency Policy (NREEEP) and the Renewable Energy Master Plan (REMP) provide a foundation for renewable energy development, aiming to boost renewable generation to 36% by 2030 [42,43]. The National Automotive Design and Development Council has launched solar-powered EV charging pilot stations in Lagos and Sokoto [22]. However, significant gaps persist between policy formulation and implementation, with only 180 charging stations (including 30 fast charging points) operational as of 2024, predominantly in urban areas [44]. These factors collectively position Nigeria as an ideal context for investigating intelligent off-grid renewable EV charging, with findings transferable to similar contexts across sub-Saharan Africa, South Asia, and Southeast Asia.

3. Hybrid Solar–Wind System Architectures

The design of off-grid EV charging stations begins with the selection of system architecture, which fundamentally determines operational characteristics, efficiency, reliability, and cost. This section analyses the principal configuration types, examines how solar and wind resources integrate within each architecture, and quantifies the synergistic benefits of hybridization that make these systems superior to single-source alternatives.

3.1. System Configuration Typologies

Hybrid renewable energy systems for EV charging can be classified into three architectural paradigms based on bus configuration: AC-coupled, DC-coupled, and hybrid

AC–DC [45,46]. Each offers distinct advantages and trade-offs. In AC-coupled architectures, renewable sources connect to a common AC bus via dedicated inverters, offering modularity and simplified integration with existing AC infrastructure but incurring multiple conversion losses (DC–AC–DC) resulting in cumulative efficiency penalties of 10–15% [47–49]. DC-coupled architectures employ a common DC bus through appropriate power electronic interfaces, eliminating multiple conversion stages and improving overall efficiency by 5–9% compared with AC-coupled alternatives [50]. Recent implementations using synchronous rectification and zero-voltage switching achieve DC–DC converter efficiencies exceeding 97%, with overall system efficiencies of 92–95% from renewable source to EV battery [51]. Hybrid AC–DC configurations maintain separate AC and DC buses coupled via intelligent bidirectional converters, accommodating both AC and DC loads while optimizing power flow based on real-time conditions [52]. Table 2 presents a comparative analysis of these configurations, and Figures 3–5 illustrate their architectures.

Table 2. Comparison of hybrid system configurations for off-grid EV charging [21,24,52–54].

Parameter	AC-Coupled	DC-Coupled	Hybrid AC–DC
System Efficiency	85–90%	92–97%	90–95%
Conversion Stages	Multiple (DC–AC–DC); higher losses	Fewer (direct DC); higher efficiency	Dual paths with smart routing
Control Complexity	Low–Moderate	Moderate–High	High
EV Charger Support	AC Level 1 & 2	DC fast charging	Both AC and DC
Capital Cost (USD/kW)	850–1100	720–920	800–1050
Best Application	Retrofit; rural microgrids with AC loads	New off-grid DC fast-charging stations	Smart hybrid stations; future microgrids

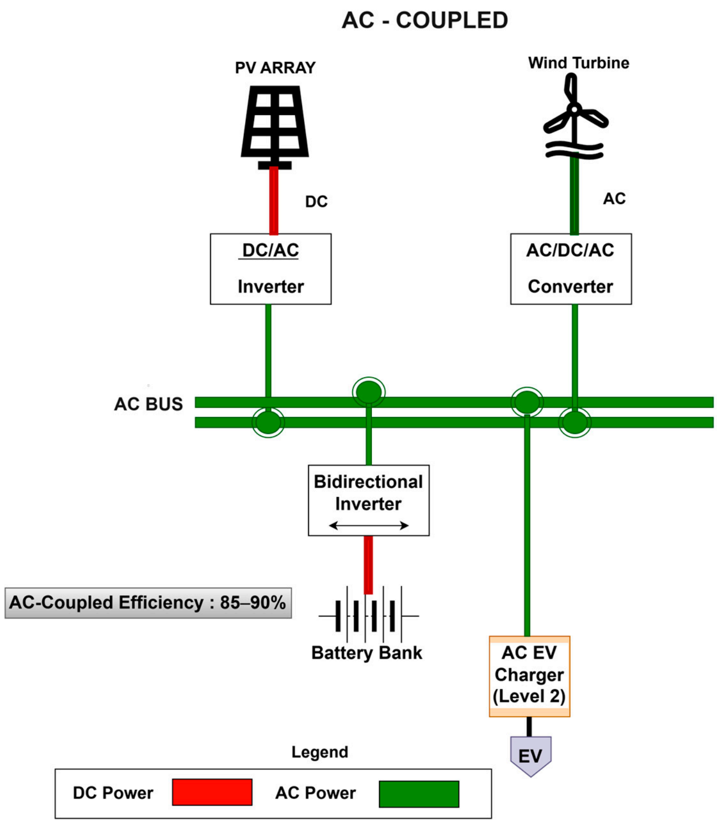

Figure 3. AC-coupled configuration.

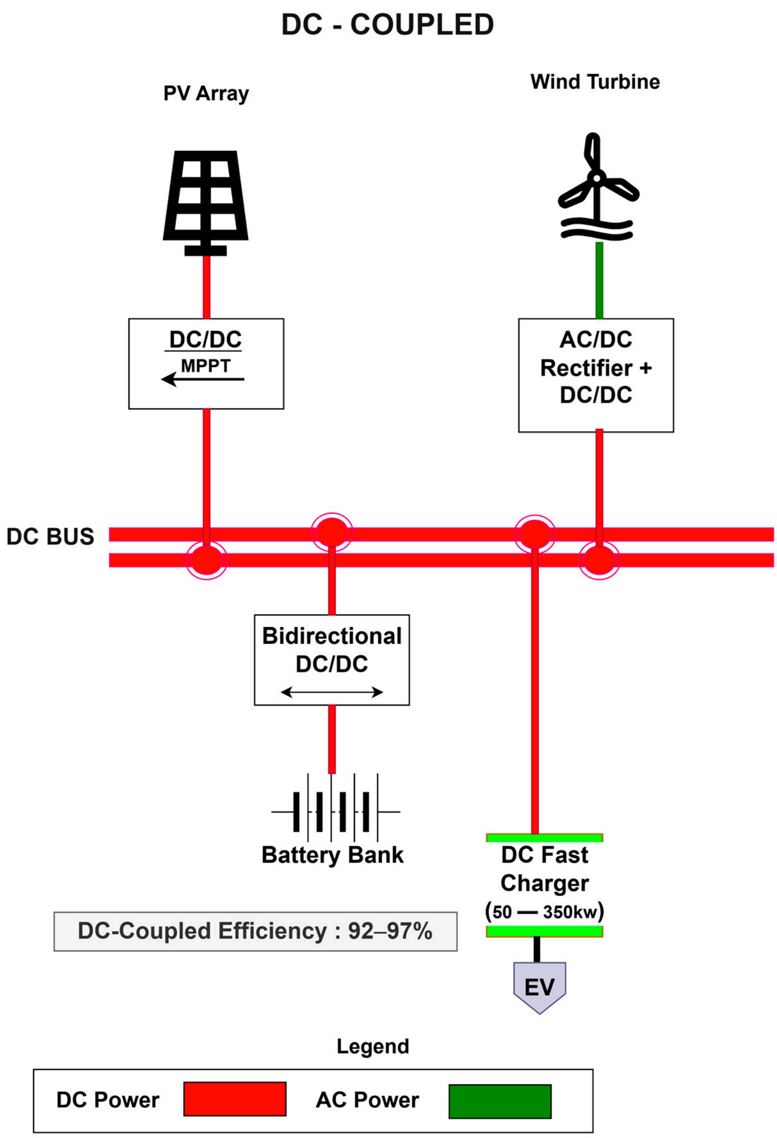

Figure 4. DC-coupled configuration.

Figures 3–5 show the hybrid solar–wind EV charging system architectures: Figure 3 shows AC-coupled configuration with grid-forming AC bus and multiple DC–AC conversions (efficiency: 85–90%), Figure 4 shows DC-coupled configuration with common DC bus enabling direct DC fast charging (efficiency: 92–97%), and Figure 5 shows hybrid AC–DC configuration with dual buses and intelligent power routing supporting both AC and DC charging (efficiency: 90–95%).

Analysis of Table 2 reveals important trade-offs when evaluated against four criteria specifically relevant to developing country deployments. First, regarding efficiency under partial load conditions: DC-coupled architectures maintain 90–95% efficiency even at 20–40% loading, whereas AC-coupled systems suffer disproportionate losses at low loads due to inverter standby consumption, dropping to 75–82% efficiency below 30% capacity [50,52]. This is critical for off-grid stations where overnight or off-peak utilization may be low. Second, regarding maintainability with limited technical expertise, AC-coupled systems benefit from familiarity—local electricians trained on conventional AC wiring can perform basic maintenance—whereas DC-coupled systems require specialized knowledge of DC protection, arc fault management, and high-voltage DC safety protocols that may not be locally available [49,50]. Third, regarding resilience to component failure, DC-coupled architectures exhibit single-point-of-failure vulnerability at the central DC bus converter;

failure of this component disables the entire station. Hybrid AC–DC configurations offer superior resilience through redundant power paths, enabling partial operation when one bus fails [52]. Fourth, regarding scalability, DC-coupled systems scale efficiently by adding parallel converter modules, while hybrid AC–DC architectures accommodate both generation expansion (additional PV/wind) and load diversification (community services) without architectural redesign [45,52]. On balance, DC-coupled systems offer the optimal combination of efficiency and cost for dedicated off-grid EV charging stations, while hybrid AC–DC configurations are preferred where charging stations also serve as community energy hubs providing lighting, telecommunications, and refrigeration services.

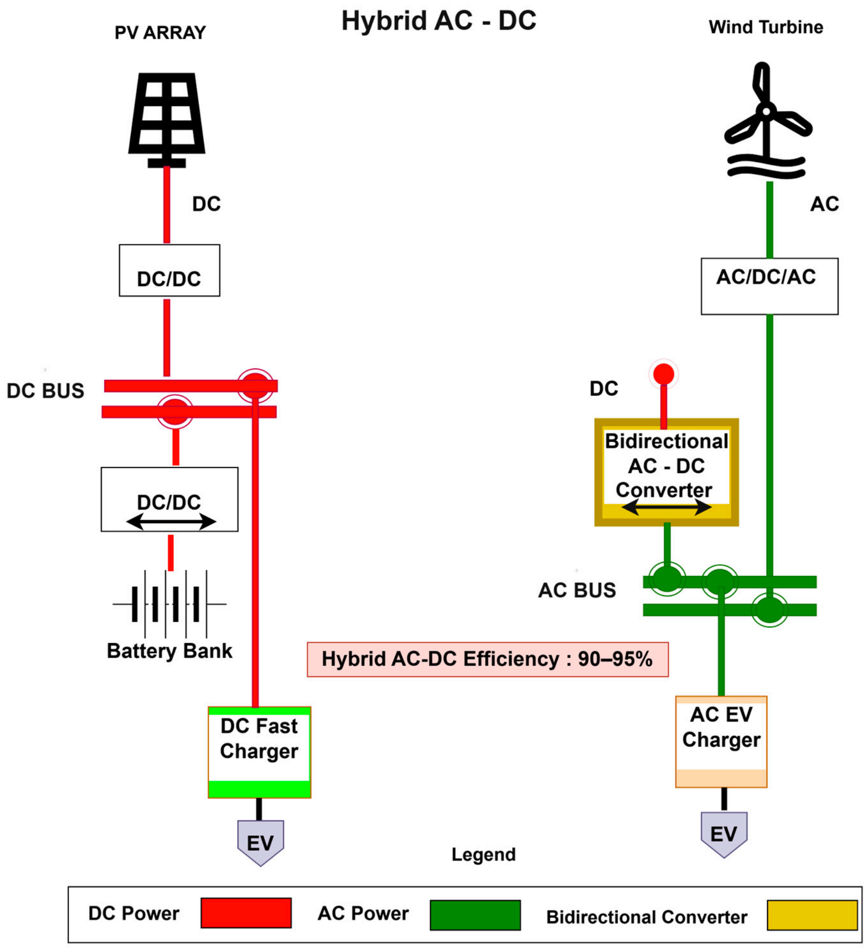

Figure 5. Hybrid AC–DC configuration.

3.2. Resource Complementarity and Hybridization Benefits

The fundamental advantage of hybrid solar–wind systems lies in temporal and seasonal resource complementarity, reducing system intermittency and battery storage requirements compared with single-source configurations [10,55,56]. Comprehensive analysis across diverse geographic locations demonstrates correlation coefficients between solar and wind generation ranging from −0.2 to −0.6, with strongest negative correlation (optimal complementarity) observed in coastal regions, mountainous terrain, and monsoon-influenced climates [10,55].

Resource complementarity manifests in two primary dimensions. Diurnal complementarity arises from typical wind speed profiles that peak during evening and nighttime hours (18:00–06:00) when solar generation is absent, driven by differential heating patterns and atmospheric boundary layer dynamics [10,56]. Seasonal complementarity varies by location: tropical regions often experience reduced solar irradiation during monsoon periods coinciding with increased wind speeds, while temperate zones may exhibit winter wind maxima during periods of reduced solar availability [55,56]. Optimal PV-to-wind capacity ratios typically range from 1:1 to 4:1, with higher ratios in tropical/subtropical regions (strong solar, moderate wind) and lower ratios in temperate coastal zones [7,9,22]. Table 3 presents comparative performance metrics demonstrating the quantitative advantages of hybridization across diverse climatic contexts.

Table 3. Comparative performance metrics: single source versus hybrid configurations [7,9,22].

Location	Config.	Yield (kW/day)	Cap. Factor (%)	Efficiency (%)	Continuity Index	LCOE (USD/kWh)	Key Observation
Nairobi, Kenya	Solar-only	42	18.4	85	0.78	0.34	High daytime, low night
	Wind-only	29	15.1	80	0.65	0.41	Poor calm-period reliability
	Hybrid	61	26.3	92	0.95	0.28	Excellent day-night balance
Nigeria (Savannah)	Solar-only	49	20.3	87	0.82	0.31	Strong solar, low dry-season wind
	Wind-only	25	12.7	81	0.68	0.40	Low inland availability
	Hybrid	64	26.9	92	0.94	0.28	Continuous supply, cost reduction
Jaipur, India	Solar-only	46	19.7	86	0.81	0.32	Strong solar, limited wind
	Hybrid	58	24.5	91	0.93	0.27	Optimal cost and high uptime

The Continuity Index (CI) quantifies system reliability as the complement of the Loss of Power Supply Probability ($LPSP$), a standard metric in off-grid renewable energy system design [7,9].

$$CI = 1 - LPSP = 1 - \left[\sum (t = 1\ to\ T)\delta(t)/T\right] \quad (1)$$

where T is the total number of time steps in the evaluation period, and $\delta(t)$ is a binary deficit indicator defined as

$$\delta(t) = 1,\ \text{if}\ P\_PV\ (t) + P\_W(t) + P\_Bd(t) < P\_load(t), \text{and}\ \delta(t)\ =\ 0\ \text{otherwise.}$$

where $P\_PV\ (t)$ is the photovoltaic output, $P\_W(t)$ is the wind turbine output, $P\_Bd(t)$ is the available battery discharge power, and $P\_load(t)$ is the EV charging demand at time step t. A CI of 1.0 indicates uninterrupted supply over the entire evaluation period, while values below 0.80 indicate frequent service disruptions. The CI values reported in Table 3 are derived from the referenced studies [7,9,22] using hourly time-step simulations over 12-month evaluation periods.

The data in Table 3 demonstrate consistent hybrid superiority across all climatic zones. Levelized cost of energy (LCOE) reductions of 15–30% compared with single-source alternatives indicate that hybrid architectures are both technically and economically feasible for off-grid EV stations. Power continuity indices consistently exceed 0.93 for hybrid systems compared with 0.65–0.82 for single-source configurations, reflecting the critical reliability advantage of resource diversification. Nigeria's solar potential is among the highest globally, but low inland wind speeds make hybridization essential for reliable 24 h charging service. These findings establish hybrid solar–wind systems as the architecture of choice for the subsequent analysis of enabling technologies (Section 4) and intelligent control strategies (Section 5).

In Figure 6, battery storage requirements are added which shows that the hybrid system requires 3 × less battery than Solar-only and 5 × less than Wind-only. Overall, the figure clearly demonstrates that integrating solar and wind resources into a hybrid system enhances system robustness and reduces dependence on large battery storage, making it a more effective solution for off-grid EV charging applications in developing regions.

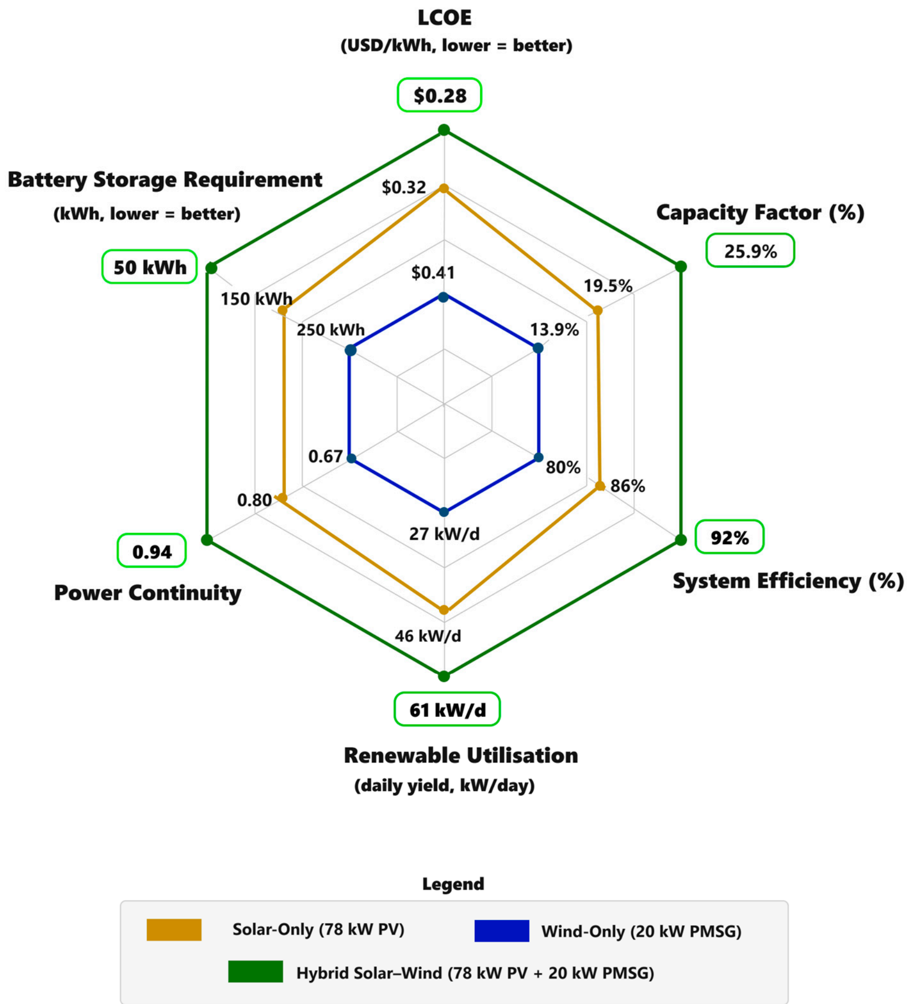

Figure 6. Radar chart comparing single-source and hybrid configurations across six performance dimensions.

4. Enabling Technologies: Power Electronics and Energy Storage

Realizing the performance advantages of hybrid solar–wind architectures depends on two enabling technology domains: power electronic converters that efficiently interface diverse generation sources with charging loads, and battery storage systems that bridge temporal mismatches between generation and demand. This section examines the state of the art in both areas, with particular attention to characteristics determining suitability for harsh, resource-constrained deployment environments.

4.1. Power Electronic Converter Technologies

Power electronic converters serve as critical interfacing components between renewable sources, storage, and EV loads, fundamentally determining overall system efficiency, power quality, and reliability [25,57]. Non-isolated boost converters dominate PV applications, stepping up typical panel voltages (30–50 V DC) to higher bus voltages (400–800 V) with efficiencies of 95–97% using silicon devices and 97–98.5% using silicon carbide (SiC) [54,58]. Interleaved boost configurations employing multiple parallel phases with phase-shifted switching offer reduced input/output current ripple, distributed thermal stress, and effective switching frequency multiplication, achieving 96–98.5% efficiency in 10–50 kW PV interfaces [54]. For battery interfaces, bidirectional DC–DC converters enable energy flow in both directions with round-trip efficiencies of 89–95%, essential for both charging and potential vehicle-to-grid functionality [59]. Isolated topologies including dual-active-bridge converters provide galvanic isolation for safety-critical applications, achieving 94–97.5% efficiency with SiC devices through zero-voltage switching [60]. Table 4 compares converter efficiencies across power ranges and semiconductor technologies.

Table 4. Power electronic converter efficiency comparison [25,58,59].

Converter Type	Power Range	Si MOSFET Efficiency	SiC Efficiency	Improvement
Boost Converter	1–10 kW	95–97%	97–98.5%	+1.5–2%
Interleaved Boost	10–50 kW	96–97.5%	97.5–98.5%	+1–1.5%
Full-Bridge Isolated	5–50 kW	94–96%	96–97.5%	+2–2.5%
Three-Phase Inverter	10–100 kW	95–97%	97.5–99%	+2–2.5%

4.2. Wide-Bandgap Semiconductor Devices

Silicon carbide and gallium nitride devices represent a paradigm shift in power electronics for renewable EV charging applications. SiC MOSFETs enable switching frequencies of 50–100 kHz (versus 10–20 kHz for silicon), reducing passive component sizes by 40–60% and improving power density [25,58]. Comprehensive studies demonstrate 1.5–2.5% higher efficiency than silicon counterparts, with advantages amplified at elevated temperatures (up to 175 °C junction temperature versus 125 °C for silicon)—a critical characteristic for tropical deployments [61,62]. Despite 2–3× higher device costs, system-level analysis indicates break-even within 3–5 years for high-utilization applications through improved efficiency (reducing energy losses by USD 150–300 per kW annually), reduced cooling requirements, and smaller magnetic components [61–63]. For developing country applications where capital costs are a primary concern, the optimal semiconductor choice depends on utilization rates: SiC is favored for stations exceeding 4000 operating hours per year, while silicon remains cost-effective for lower-utilization installations [63]. GaN devices target lower-voltage applications (<650 V) at frequencies up to 1 MHz, offering potential for ultra-compact auxiliary converters, though limited voltage ratings currently restrict their role in off-grid EV charging systems [59].

4.3. Battery Energy Storage Technologies

Battery storage constitutes the critical bridging element between intermittent renewable generation and variable EV charging demand, enabling power smoothing, load shifting, and continuous operation during periods of insufficient renewable output. Multiple chemistries compete for stationary storage applications, each presenting distinct trade-off. Table 5 compares key characteristics.

Table 5. Battery technology comparison for stationary storage in off-grid EV charging [8,33].

Technology	Energy Density (Wh/kg)	Cycle Life	Efficiency (%)	Cost (USD/kWh)	Key Advantage	Best Application
LFP	90–120	3000–5000	95–98	100–150	Safety, long life	Hot climates (recommended)
NMC (Nickel Manganese Cobalt)	150–220	1500–3000	90–95	120–180	High energy density	Space-constrained sites
Lead-Acid (VRLA)	30–50	500–1200	70–85	50–100	Low cost, mature	Budget-constrained projects
VRFB (Vanadium redox flow battery)	20–35	10,000+	65–85	300–500	Unlimited DOD cycling	Long-duration, large-scale

For developing country applications, lithium iron phosphate (LFP) batteries offer the optimal balance of cost, safety, and performance. LFP's excellent thermal stability (no thermal runaway up to 270 °C), long cycle life (3000–5000 cycles at 80% depth of discharge), and declining costs (USD 100–150/kWh in 2024) make it the preferred chemistry for stationary storage in hot climates common across sub-Saharan Africa and South Asia [8,33]. However, battery degradation under harsh operating conditions remains a critical concern. Capacity fade accelerates exponentially with temperature (2.4× faster at 45 °C versus 25 °C), high state-of-charge (2–3× faster at 100% versus 50% SOC), and high charge rates (40% fewer cycles at 1C versus 0.3C) [64,65]. Optimal operating windows of 20–80% state of charge (SOC) can double cycle life, while active thermal management extending battery operating life from 6 to 11 years yields net lifecycle savings of approximately USD 5730 (28% reduction) for a 100-kWh installation [65,66]. Critically, idealized models that neglect these degradation dynamics overestimate energy delivery by 10–15% and underestimate lifecycle costs by 25–35%, underscoring the importance of incorporating temperature-dependent aging, SOC-dependent fade, and C-rate-dependent cycle loss into realistic system planning for tropical deployments [64–66]. For hybrid solar–wind systems, battery capacity requirements are typically 30–50% less than equivalent single-source PV configurations due to improved resource complementarity [9,55]. These degradation dynamics directly motivate the intelligent energy management strategies examined in Section 5, where degradation-aware control is essential for economic viability.

5. Intelligent Energy Management and Control Strategies

Intelligent energy management systems (EMS) represent the critical enabling layer that transforms hybrid solar–wind hardware into reliable, economically viable EV charging infrastructure. The EMS optimizes power flow between renewable sources, storage, and charging loads while maintaining system stability and minimizing operational costs. This section analyses the taxonomy of control approaches, examines their suitability for off-grid developing country contexts, and presents advanced distributionally robust optimization frameworks designed for data-scarce environments with extreme uncertainties. The classification progresses from simple rule-based approaches through optimization-based methods (LP, MILP, DP, MPC) and AI-based strategies (fuzzy logic, ANFIS, reinforcement learning, deep learning) to advanced distributionally robust optimization (DRO) frameworks that address data scarcity are illustrated in Figure 7. Performance improvement ranges and computational requirements are indicated for each category.

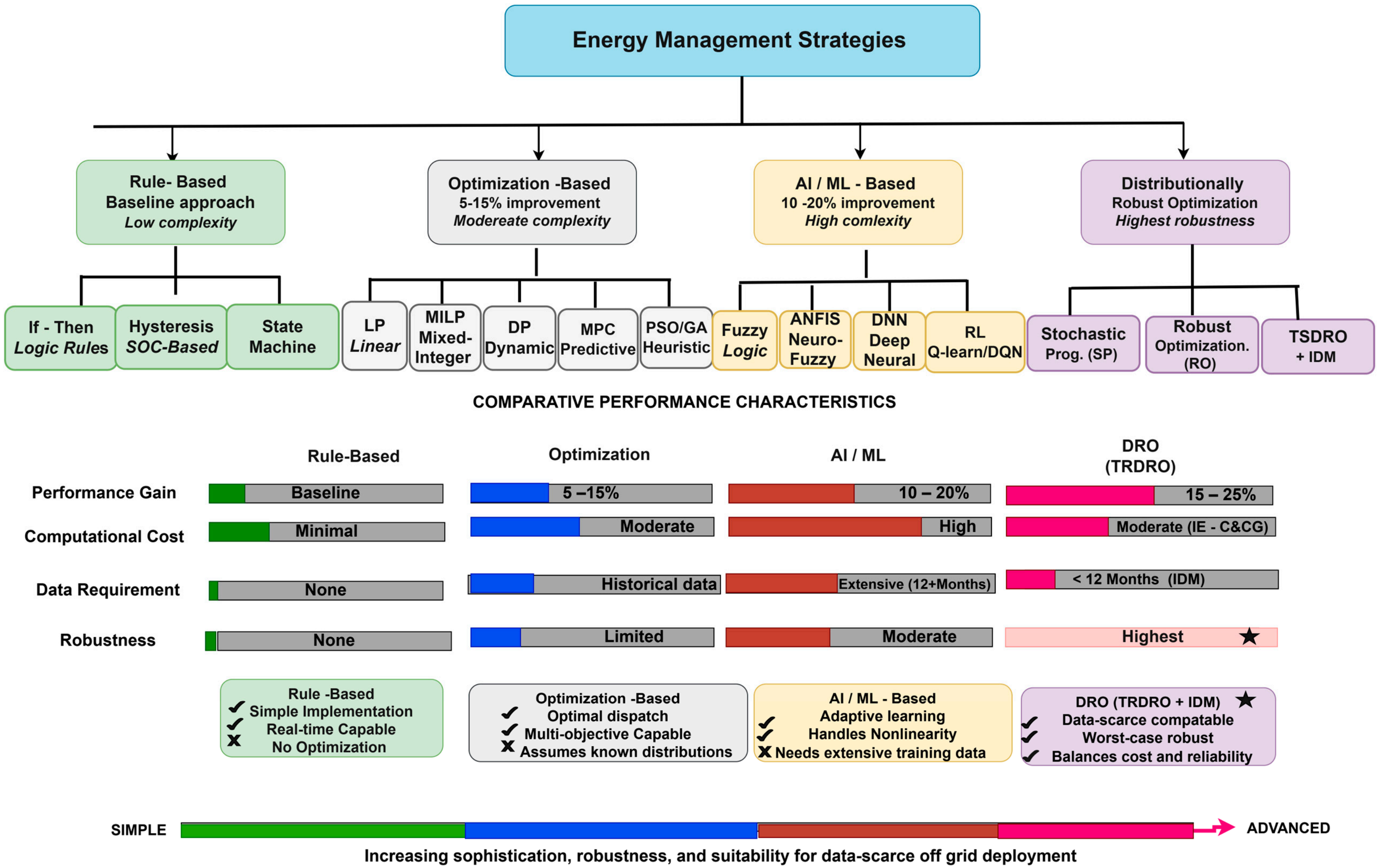

Figure 7. Taxonomy of energy management strategies for hybrid renewable EV charging systems.

5.1. Hierarchical Control Architecture

Energy management in hybrid systems employs hierarchical control organized into three layers operating at different time scales [67,68]. The primary control layer (microsecond–millisecond) provides fast local control of individual converters including droop control, maximum power point tracking (MPPT) for PV and wind, and battery charge/discharge regulation. The secondary control layer (seconds–minutes) handles voltage and frequency restoration, power quality enhancement, and load sharing among distributed resources through communication-based coordination. The tertiary control layer (minutes–hours) manages long-term optimization including energy arbitrage, demand forecasting, and economic dispatch using predictive algorithms and optimization solvers [67,68]. This hierarchical structure enables both fast response to transient events and long-horizon strategic optimization, which is essential for managing the dual uncertainties of renewable generation and EV charging demand. Figure 8 shows the hierarchical control architecture for hybrid solar–wind EV charging systems showing three control layers: primary (local converter control, μs–ms), secondary (coordination and power quality, s–min), and tertiary (optimization and forecasting, min–hours).

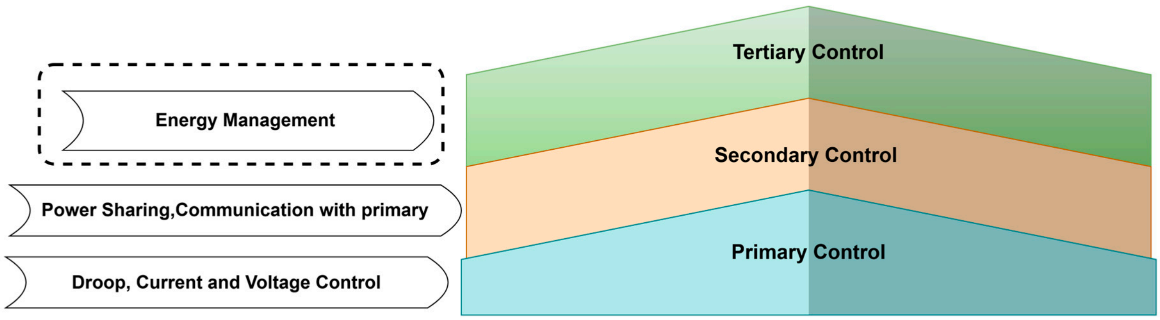

Figure 8. Hierarchical control architecture.

5.2. Energy Management Approaches: Comparative Analysis

Rule-based strategies employ predefined logic to determine power flow based on battery SOC, renewable availability, and load demand [15,69]. While offering simplicity, real-time implementation capability, and deterministic behavior suitable for small systems with predictable loads, they lack optimization capability and struggle to adapt to varying conditions. Optimization-based strategies formulate energy management as constrained optimization problems using linear programming, mixed-integer linear programming (MILP), or dynamic programming, minimizing costs while satisfying reliability constraints [55,70]. Model predictive control (MPC) extends optimization over receding horizons incorporating forecasts, enabling proactive decision-making [15,66]. AI-based strategies leverage machine learning to learn optimal policies from data: reinforcement learning agents adapt through environment interaction, deep Q-networks handle high-dimensional state spaces, and fuzzy logic controllers address inherent uncertainties and nonlinearities in renewable generation and EV demand [11,14,16,71]. While these conventional approaches demonstrate effectiveness for typical operational uncertainties, they exhibit significant limitations when confronting extreme source-load uncertainties and data scarcity characteristic of off-grid deployments in developing regions. Table 6 provides a comparative analysis of representative optimization approaches from the literature, revealing critical gaps that motivate the advanced frameworks discussed in Section 5.3.

The studies in Table 6 are categorized into two distinct groups (a “Methodological” vs. “Application” classification): methodological contributions that advance optimization theory on two-stage robust optimization [26]. Application-based evaluations are those that validate existing methods in specific deployment contexts. They are multi-objective deep RL [72], heuristic sizing in rural India [73], MILP for Kenyan wind systems [6], and grasshopper optimization for Nigerian community sizing [74]. This distinction is important because methodological contributions are potentially transferable across contexts, whereas application-based findings are site-specific and may not generalize. A cross-cutting observation is that no study in Table 6 simultaneously addresses all three requirements for practical off-grid deployment: uncertainty-aware optimization, degradation modelling, and hybrid resource complementarity. Six principal limitations emerge from Table 6 that constrain applicability to standalone hybrid solar–wind EV charging in resource-constrained contexts. First, single-source systems sacrifice reliability, necessitating oversized storage (3–5$\times$ capacity) that increases costs by 40–60% [26,73]. Second, studies incorporating diesel or biomass introduce fuel dependency inappropriate for remote areas lacking supply chains [75]. Third, deterministic methods fail under renewable variability, with field studies reporting 15–30% capacity shortfall during unfavorable weather, whereas robust approaches over-conservatively oversize components by 18–25% [26,74]. Fourth, stochastic programming requires accurate probability distributions unavailable in data-scarce regions where operational datasets may span less than 12 months [17,76]. Fifth, most studies neglect battery degradation and converter losses, leading to 25–40% lifecycle cost underestimation, particularly critical in hot climates where aging accelerates 2.4–5.7$\times$ [64–66]. Sixth, none exploit the temporal complementarity between solar and wind generation that increases effective capacity factor from 35–45% (single source) to 58–68% (hybrid). These gaps collectively motivate the TSDRO framework presented in the following section.

Table 6. Comparative analysis of optimization approaches for off-grid hybrid solar–wind EV charging.

Reference	Year	Context	Sources	Method	Main Finding	Key Limitation
Kumar et al. [73]	2020	Rural India	PV only	Heuristic (PSO)	LCOE USD 0.18/kWh	No wind; single source limits reliability
Ogutu et al. [6]	2023	Rural Kenya	Wind only	MILP	100% wind penetration	Vulnerable to calm periods; deterministic
Adefarati et al. [75]	2024	Off-grid Nigeria	PV + Diesel	Genetic Algorithm	Diesel reduced 72%	Diesel dependency persists; no uncertainty
Li et al. [26]	2024	Island microgrid	PV + Wind	Two-stage RO	99% reliability	Over-conservative (18–25% higher cost)
Bhavani et al. [76]	2026	Rural communities	PV + Wind	Stochastic prog.	Hybrid storage: 35% less stress	Requires accurate distributions
Abid et al. [72]	2024	Bangladesh	PV + Wind	Deep RL (DDPG)	28% improved battery life	Short-term; extensive training data needed
Hassan et al. [17]	2024	Sub-Saharan Africa	PV + Wind	MPC	Real-time; 62% RE fraction	Requires perfect forecasts; no robustness
Araoye et al. [74]	2024	Nsukka Community, Nigeria	PV + Wind	GOA	Optimal sizing; USD 0.19/kWh	Fails under variability; no degradation

5.3. Two-Stage Distributionally Robust Optimization Framework

Two-stage distributionally robust optimization emerges as a methodology that synthesizes the advantages of stochastic programming and robust optimization while mitigating their respective drawbacks [17–20]. Unlike stochastic programming, which assumes a known probability distribution, and robust optimization, which considers only worst-case scenarios, TSDRO optimizes against the worst-case distribution within a defined ambiguity set—a family of probability distributions centered around available data [17–20].

Framework Structure

The TSDRO framework decomposes the optimization into two sequential stages. In the first stage, day-ahead scheduling determines all here-and-now decisions based on available forecast information, including battery charging and discharging schedules, thermal energy storage management, and scheduled EV charging capacity allocation. Because these decisions are made before uncertainty is realized, they must be robust against the range of scenarios captured in the ambiguity set. In the second stage, intra-day rescheduling addresses wait-and-see decisions that respond to realized uncertainties, including real-time power balancing between solar, wind, and battery systems, dynamic EV charging rate adjustment, and emergency load shedding protocols [17,18]. The mathematical formulation is expressed as

$$Min_{\chi \epsilon X}\{C^T\chi + Sup_{P\epsilon D}E_P[Q(\chi,\xi)]\} \tag{2}$$

where x represents first-stage decision variables (day-ahead schedule), ξ denotes uncertain parameters (solar/wind generation, EV demand, temperature), $Q(x, \xi)$ is the second-stage recourse cost function, D is the distributional ambiguity set, and the supremum captures worst-case expectation over all distributions in D.

Two-stage distributionally robust optimization framework for off-grid hybrid solar–wind EV charging. Stage 1 (day-ahead) determines battery schedules, thermal storage management, and EV capacity allocation using forecast data. Uncertainty realization then reveals actual solar/wind output and EV demand. Stage 2 (intra-day) adjusts power balancing, charging rates, and load shedding based on realized conditions. The Imprecise Dirichlet Model constructs the ambiguity set D from limited historical data, and the IE-C&CG algorithm solves the resulting tri-level optimization.

5.4. Imprecise Dirichlet Model for Data-Scarce Environments

For hybrid solar–wind systems deployed in data-scarce developing regions, the Imprecise Dirichlet Model (IDM) provides an effective framework for constructing uncertainty sets from limited historical data (see purple panel in Figure 9) [17,77]. Remote off-grid stations in Nigeria, Kenya, or rural sub-Saharan Africa typically lack comprehensive datasets, with data collection periods often spanning less than 12 months. The IDM addresses this by partitioning the uncertain parameter space into discrete scenarios, constructing lower and upper probability bounds for each partition based on limited observations, and forming a credal set containing all distributions consistent with observed data. For n observations distributed across K bins, the lower probability bound for bin k is P_L(B_k) = n_k/(n + s) and the upper bound is P_U(B_k) = (n_k + s)/(n + s), where the hyperparameter s ∈ [1,2] controls conservatism [17,77]. Three primary uncertainty sources require IDM modelling: solar PV output (affected by cloud cover, dust accumulation, and panel degradation), wind power output (influenced by seasonal patterns and terrain effects), and EV charging demand (dependent on mobility patterns and fuel prices). These are combined into a joint ambiguity set capturing their correlation structure through a prescribed copula [17,18].

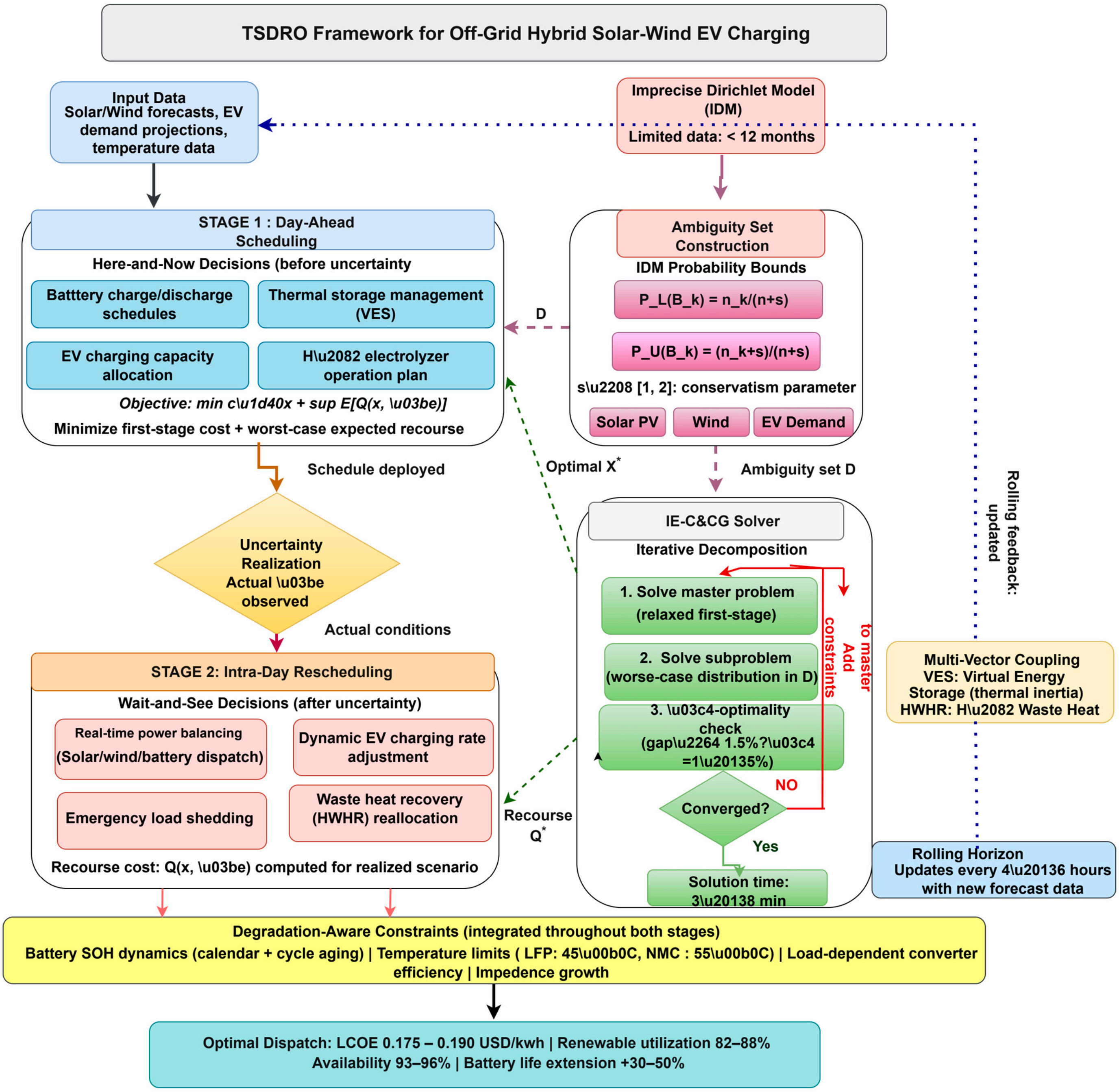

Figure 9. Two-stage distributionally robust optimization (TSDRO) framework for off-grid hybrid solar–wind EV charging systems. X^* represents the optimal stage 1 decision obtained from the DRO model, and Q^* represents the optimal recourse cost from the stage 2.

5.5. Multi-Vector Energy Coupling

Advanced TSDRO implementations extend beyond electrical energy management to exploit multi-vector energy coupling, specifically virtual energy storage (VES) and hydrogen waste heat recovery (HWHR) [17,78]. VES leverages the thermal inertia of building enclosures, thermal storage systems, and controllable thermal loads to provide indirect electrical storage without additional battery investment. For off-grid stations in extreme climates (e.g., Nigeria's 38–42 °C summers), VES pre-conditions thermal storage during excess generation periods, effectively storing electrical energy as thermal energy. During renewable scarcity, reduced thermal loads release capacity for EV charging. Hydrogen systems generate significant waste heat during electrolysis (40–50% efficiency loss as heat) and fuel cell operation (50–60% loss); HWHR captures this waste heat for battery thermal management, space conditioning, and dehumidification [17,78]. Integration of VES and HWHR has been demonstrated to reduce carbon emissions by 23.4% while improving renewable utilization from 67.2% to 84.6% compared with electrical-only optimization [17]. The concept of virtual storage has broader parallels in highly coupled energy systems. Recent work on spatio-temporal coordinated operation of data centers demonstrates that computational load flexibility can serve as virtual storage to handle extreme uncertainties in renewable-powered systems [79]. While data center approaches exploit spatial and temporal migration of computational workloads, off-grid EV charging stations can analogously exploit building thermal inertia and controllable thermal loads to buffer electrical energy, a principle that enriches the theoretical foundation of the VES approach in our framework.

5.6. Computational Tractability via IE-C&CG

The TSDRO formulation with IDM-based ambiguity sets creates a complex tri-level optimization problem that is intractable for direct solution. The Inexact Enhanced Column-and-Constraint Generation (IE-C&CG) algorithm provides computational efficiency by iteratively decomposing the problem into a master problem and subproblem [17,19,20]. The subproblem is solved to within τ-optimality (τ = 1–5%) rather than exactly, reducing solution time by 60–80% with negligible impact on quality. For a typical off-grid station (15 kW PV, 5 kW wind, 30 kWh battery), IE-C&CG reduces solution time from 45–120 min (branch-and-bound) to 3–8 min with solution gaps below 1.5%, enabling day-ahead scheduling, rolling-horizon updates every 4–6 h, and rapid scenario analysis on standard computing hardware [17,20].

5.7. Degradation-Aware Formulation

The TSDRO framework incorporates conversion losses and battery aging for realistic operational planning [17,64,66]. The objective function includes degradation costs alongside operating costs, and the power balance constraint accounts for load-dependent converter efficiencies and temperature-dependent battery efficiencies. Battery state-of-health dynamics capture both calendar aging (driven by temperature and SOC) and cycle aging (driven by depth of discharge and C-rate), while power limits decrease with aging through impedance growth. Thermal constraints maintain cell temperatures below 45 °C for LFP and 55 °C for NMC chemistries. This integrated formulation prevents the systematic errors inherent in idealized models, which overestimate energy delivery by 10–15% and underestimate costs by 25–35% [64–66].

5.8. Application Potential for Developing Regions

Applying the TSDRO-IDM framework to the Nigeria Sokoto station configuration (174 kW PV, two wind turbines, 380 batteries, 109 kW converter [22]) yields projected improvements over rule-based control: LCOE reduction of 17–21% (from USD 0.211 to USD 0.175–0.190/kWh), renewable utilization improvement of 20–29% (from 68% to 82–88%), system availability improvement of 6–9 percentage points (from 87% to 93–96%), and battery replacement cycle extension of 30–50% through improved thermal management [17,22,78]. The total implementation cost of USD 15,000–25,000 (including industrial computing hardware, software development, and operator training) yields payback periods of 18–30 months. The framework is particularly compelling for addressing operational challenges documented in Section 7, including Harmattan dust impacts (TSDRO anticipates reduced PV output and optimally allocates battery/wind resources), temperature extremes (VES pre-conditioning reduces peak thermal loads by 30–40%), and revenue volatility (distributional robustness maintains profitability across the demand uncertainty range).

6. Artificial Intelligence and Machine Learning Applications

AI and machine learning techniques provide essential capabilities across the hybrid renewable EV charging system lifecycle, from resource forecasting through operational optimization to predictive maintenance. This section examines key applications with emphasis on performance in data-scarce developing country contexts. Table 7 synthesizes the principal ML applications and their demonstrated benefits.

Table 7. Machine learning applications in hybrid renewable EV charging systems [11,14,16,69,71].

Application	ML Technique	Accuracy/Performance	Benefit for Off-Grid Systems
Solar Forecasting (1-h)	LSTM, CNN-LSTM	MAPE: 10–15% (clear); 20–30% (cloudy)	Proactive battery management; reduced cycling
Wind Forecasting (1-h)	Ensemble methods, LSTM	MAPE: 15–25%	Improved dispatch planning for complementary generation
Load Forecasting (day-ahead)	RNN, GRU, Transformers	MAPE: 8–12%	Optimized charging schedules; peak demand reduction
Charging Optimization	Deep RL (DQN, A3C)	10–20% cost reduction	Adaptive policy learning without explicit programming
Anomaly Detection	Autoencoders, Isolation Forest	F1-score: 0.85–0.95	Early fault detection; 15–25% downtime reduction
RUL Prediction	RNN, Survival Analysis	MAE: 5–10% of lifetime	Condition-based maintenance; optimized replacement timing

Solar and wind forecasting using LSTM and CNN-LSTM architectures achieve mean absolute percentage errors of 10–15% and 15–25%, respectively, for short-term predictions, enabling proactive energy management that reduces battery cycling and improves renewable utilization by 8–12% [14,16]. Load forecasting using recurrent neural networks and transformer architectures achieves 8–12% MAPE for day-ahead predictions [14]. Reinforcement learning-based charging optimization achieves 10–20% cost reductions compared with rule-based strategies through adaptive policies that respond dynamically to changing conditions [66,71]. Anomaly detection using autoencoders and isolation forests achieves F1 scores of 0.85–0.95, enabling early fault identification that reduces downtime by 15–25% [11,80]. Remaining useful life prediction supports condition-based maintenance scheduling with mean absolute errors of 5–10% of component lifetime [66,80].

Practical deployment in developing countries requires addressing several challenges that differentiate techniques by their data requirements and deployability. Techniques can be divided into two categories based on data dependency. Data-intensive methods—including deep reinforcement learning (DQN, A3C), CNN-LSTM forecasting, and transformer-based load prediction—achieve the highest accuracy (MAPE 8–15%) but require 12–24 months of high-resolution operational data for training, a prerequisite rarely met at newly commissioned off-grid stations [14,16]. In contrast, data-efficient methods—including transfer learning, few-shot learning, and physics-informed neural networks—can achieve 70–85% of peak performance with as little as 2–4 weeks of site-specific data by leveraging pre-trained models from similar installations or embedding known physical constraints (energy balance, PV characteristic curves) directly into the learning architecture [11,71]. For initial deployment in data-scarce developing country contexts, a staged approach is recommended: rule-based control during the first 3–6 months of data collection, transitioning to transfer-learning-enhanced strategies as sufficient local data accumulates, and finally to fully data-driven methods once 12+ months of operational records are available. Additional practical requirements include model explainability for regulatory acceptance, and computational efficiency enabling implementation on edge devices with limited processing capability [14,16,71]. Emerging approaches combining fast sliding-mode observers with Kalman steady-state refinement achieve below 1.5% SOC estimation error across 0–100% SOC and −20 °C to 55 °C temperature ranges while maintaining computational tractability on low-cost microcontrollers (USD 10–30) [81,82]. Digital twin technologies creating virtual battery replicas through IoT connectivity show promise for advanced diagnostics and predictive maintenance, though intermittent connectivity in remote areas necessitates edge autonomy with store-and-forward buffering for cloud synchronization [83,84].

7. Techno-Economic Viability and Deployment Experience

The economic viability of hybrid solar–wind off-grid EV charging ultimately determines whether these systems transition from research demonstrations to widespread deployment. This section analyses economic competitiveness, examines real-world deployment experience including implementation challenges and operational data gaps, and identifies financing mechanisms for scaling deployment.

7.1. Economic Competitiveness

Hybrid solar–wind systems achieve the lowest LCOE among renewable configurations and are increasingly competitive with conventional alternatives. Table 8 compares the economic performance of energy sources for off-grid EV charging.

Table 8. Economic comparison of energy sources for off-grid EV charging [5,7,9].

System Type	Capital (USD/kW)	O&M (USD/kW/yr)	LCOE (USD/kWh)	Payback (yr)	CO_2 (kg/kWh)
Diesel Generator	800–1200	150–250	0.20–0.40	N/A	0.8–1.2
PV + Battery	2500–3500	40–80	0.12–0.18	8–12	0.05–0.10
Wind + Battery	2800–4000	60–100	0.11–0.17	7–11	0.04–0.08
Hybrid PV-Wind + Battery	2200–3200	50–90	0.08–0.15	6–10	0.03–0.06
Grid Extension	1500–2500	30–60	0.15–0.30	10–20	0.4–0.8

The hybrid configuration achieves the lowest LCOE (USD 0.08–0.15/kWh) and shortest payback period (6–10 years) among renewable options, while delivering substantially lower lifecycle costs than diesel generation. Although initial capital investment (USD 2200–3200/kW) exceeds diesel generators (USD 800–1200/kW), significantly lower operating costs (USD 50–90/kW/yr versus USD 150–250/kW/yr) and zero fuel expenses yield superior long-term economics. Environmental benefits are equally compelling: 0.03–0.06 kg CO_2/kWh compared with 0.8–1.2 kg/kWh for diesel, representing 80–95% emissions reduction. Multi-dimensional benefit analysis of off-grid hybrid stations reveals advantages extending beyond environmental impact. Economically, Kenya e-motorcycle pilot projects demonstrated 30–40% operating cost reductions for riders, translating to household income increases of 15–25% [5,9]. Socially, off-grid charging stations functioning as community energy hubs provide ancillary services—lighting, telecommunications, and cold-chain refrigeration—extending energy access to surrounding communities beyond transportation electrification. From a public health perspective, displacement of diesel generators reduces local concentrations of $PM_{2.5}$, carbon monoxide, and nitrogen oxides in communities where vehicle emissions already exceed WHO permissible limits [40,41]. However, accurate economic analysis must account for degradation: realistic LCOE models incorporating time-varying converter efficiency and battery aging yield values approximately 39% higher than idealized models, underscoring the importance of degradation-aware optimization as discussed in Section 5.3 [64,66].

Furthermore, multi-service station models that integrate EV battery charging, battery swapping, and hydrogen refueling within a single photovoltaic-supported facility offer additional revenue diversification pathways that can improve the economic viability of off-grid deployments [85]. Such all-in-one station concepts are particularly relevant for developing country contexts where maximizing the utilization of capital-intensive renewable infrastructure through multiple service offerings can significantly reduce payback periods. Innovative financing mechanisms address the capital-intensive nature of these projects in developing countries. Pay-as-you-go models spread costs through mobile payment systems, eliminating large upfront expenditures [9,23]. Energy-as-a-service models transfer ownership to third-party providers, with customers paying for consumption rather than infrastructure [23]. Public–private partnerships combine government support (land, regulatory streamlining, revenue guarantees) with private-sector capital and expertise [23]. International climate funds including the Green Climate Fund provide concessional financing for projects in least-developed countries [5,23]. Quantitative comparison of these financing mechanisms reveals significant differential impacts on project economics (see Table 9). Pay-as-you-go (PAYG) models reduce effective upfront costs by 60–80% for end-users but require mobile money penetration exceeding 40%, a prerequisite met in Kenya (83%) and Nigeria (64%) but not in many rural sub-Saharan contexts. Energy-as-a-service (EaaS) structures reduce project LCOE by 15–25% through risk-sharing between operators and consumers but require stable regulatory environments with enforceable power purchase agreements. Public–private partnerships (PPPs) leverage government support (land allocation, regulatory streamlining, revenue guarantees) alongside private capital, with documented LCOE reductions of 20–30% in pilot projects. Green Climate Fund concessional financing at interest rates of 0.25–0.75% reduces LCOE by 20–30% compared with commercial lending rates of 12–18% typical in sub-Saharan Africa. Cross-country policy analysis indicates significant variation in policy support: Nigeria and Kenya have introduced import duty exemptions for renewable equipment (reducing effective component costs from 70–80% above international prices to 0–5%), while India's FAME II scheme and Rwanda's results-based financing program demonstrate how dedicated EV strategies with clear regulatory frameworks and targeted incentives materially affect project economics, reducing LCOE by an estimated 15–25% compared with countries lacking such frameworks.

Table 9. Comparative analysis of financing mechanisms for off-grid hybrid EV charging deployment [5,9,22,23].

Mechanism	Capital Structure	Prerequisites	LCOE Impact	Scale	Risk
PAYG	60–80% upfront cost reduction for users	Mobile money penetration > 40%	Neutral (shifts cost, not reduces)	Small (1–10 kW)	Default risk; requires reliable mobile infrastructure
EaaS	Third-party ownership: user pays per kWh	Creditworthy operator; regulatory clarity	15–25% reduction via risk-sharing	Medium (10–100 kW)	Operator financial viability
PPP	Gov. support + private capital	Stable regulatory framework; gov. capacity	15–25% reduction	Large (100+ kW)	Political risk; contract enforcement
GCF	Concessional loans at 0.25–0.75%	Country accreditation; project pipeline	20–30% reduction vs commercial rates	Large	Lengthy approval (12–24 months)

7.2. Deployment Experience: Case Studies

Real-world deployment experience, while limited in published literature, provides invaluable insights into practical feasibility. In Nigeria, a study of six sites found that an optimally configured PV/wind turbine/battery station in Sokoto (174 kW PV, 2 wind turbines, 380 batteries, 109 kW converter) achieved a net present cost of USD 547,717, electricity cost of USD 0.211/kWh, and initial cost of USD 449,134 [22]. In Kenya, pilot projects deploy hybrid solar–wind systems (15 kW PV, 5 kW wind, 30 kWh battery, four Level 2 charging points) for electric motorcycle (boda-boda) charging, achieving LCOE of USD 0.12/kWh compared with USD 0.35/kWh for diesel, with payback periods of 7–9 years [5,9]. Social impact assessments reveal 30–40% reductions in operating costs for e-motorcycle operators, increasing household incomes by 15–25% [5,9]. Pacific island deployments demonstrate 35–50% lifecycle cost savings versus diesel, with 200–300 tons of CO_2 avoided annually per 100 kW installed capacity [5].

7.3. Implementation Challenges and Practical Solutions

Despite promising projections, real-world deployment faces significant operational challenges rarely documented in published literature. In the Kenya project, a local technical capacity deficit initially resulted in average repair response times of 7–10 days and service costs exceeding USD 800–1200 per incident. A structured capacity-building program training eight local technicians through a six-week intensive curriculum reduced response times to 2–3 days and costs to USD 150–300, though 18–20% of service calls still require external escalation [5,9]. Spare parts supply chain constraints present equally critical challenges: a wind turbine controller failure at the Nigeria Sokoto station required 77 days to resolve (international shipping plus customs clearance), resulting in approximately USD 3850 in lost revenue. Import duties of 20–35% plus VAT can increase component costs by 70–80%. Multi-faceted solutions including local spare parts inventory (USD 12,000 initial investment), regional parts hubs, and alternative suppliers in China and India reduced average lead times from 58 to 12 days and critical downtime by 78% [22].

Extreme weather conditions present persistent operational challenges. The Nigeria station experienced 25–35% PV output reductions during Harmattan season dust loading, bearing failures in wind turbines, and 12 inverter thermal shutdowns in one month. The Kenya station suffered USD 8400 in flood damage during unprecedented rainfall. Solutions including automated PV cleaning systems, IP65-rated enclosures, elevated battery installations, and liquid cooling loops reduced Harmattan power losses to 12–15%, eliminated bearing failures, cut thermal shutdowns by 90%, and achieved zero subsequent flooding incidents [5,9,22]. Revenue volatility of ±26% required robust cash flow management, while actual operating costs of 55–65% of revenue consistently exceeded initial projections of 5–10% [5,9,22]. Three cross-cutting practical challenges warrant emphasis. Regarding scalability, the transition from single-station pilot projects to multi-station networks requires modular architecture design using standardized components (pre-configured PV-battery-converter modules in 5–10 kW increments) that can be replicated without site-specific engineering, regional service hub models that provide shared spare parts inventory and technical support across 10–20 stations within a 200 km radius, and standardized monitoring and control platforms enabling remote diagnostics and fleet management [5,9]. Regarding long-term reliability, published MTBF data for off-grid renewable EV charging components are virtually absent from the literature; the Nigeria and Kenya experiences suggest that inverters and charge controllers are the most failure-prone components (3–4 incidents per year per station), while PV panels and battery banks exhibit fewer but more costly failures. Preventive maintenance protocols—including quarterly electrical inspections, bi-annual battery capacity testing, and automated PV cleaning schedules—reduced unplanned downtime by 60–70% at the Kenya station [5,9]. Regarding long-term financial sustainability, projects should anticipate operating costs 2–3× higher than initial feasibility study estimates, budget 12–24 months for supply chain optimization before achieving target economics and maintain cash reserves equivalent to 6 months of operating expenses to weather demand volatility and equipment failures [5,22].

7.4. Operational Data Gaps

The published literature exhibits significant data gaps that limit its utility for future deployments. Table 10 summarizes available versus missing operational data from key case studies, highlighting the critical need for standardized performance monitoring, systematic data collection, and transparent reporting.

Table 10. Summary of operational data availability from key case studies [5,9,22].

Performance Metric	Nigeria (Sokoto)	Kenya (Boda-Boda)	Industry Target
Operational period documented	<12 months (est.)	<12 months (est.)	≥24 months
Overall system uptime (%)	Not reported	Not reported	≥95%
Component MTBF (hours)	Not reported	Not reported	Documented by type
Battery SOH progression	Not reported	Not reported	>90% at 12 months
Actual LCOE (USD/kWh)	0.211 (reported)	0.12 (reported)	<0.15
O&M costs (% of revenue)	Not reported	Not reported	<30%
Climate-specific degradation	Qualitative only	Qualitative only	Quantified rates

The predominance of missing data in Table 10 underscores a fundamental gap: most published studies report initial commissioning results or short-term performance over 3–6 months, insufficient for capturing seasonal cycles, degradation trends, long-term reliability, and actual economic performance against projections. Future deployments should adopt standardized monitoring frameworks, contribute to open-access operational data repositories, and establish longitudinal research partnerships enabling systematic data collection over 3–5-year horizons. Transparent reporting of failures and challenges—not only successes—would accelerate collective learning and enable more realistic planning for new installations, which should anticipate operating costs 2–3× higher than initial projections and 12–24 months for supply chain optimization [5,9,22].

8. Research Gaps and Future Directions

Despite substantial progress, significant research gaps persist. This section synthesizes gaps identified throughout the review and charts emerging directions. Figure 10 presents a visual research roadmap. Near-term priorities (1–3 years) shows field validation of TS-DRO frameworks, standardized operational monitoring and, climate-specific degradation studies. Medium-term goals (3–5 years) shows edge AI for autonomous operation, digital twin integration, vehicle-to-grid (V2G) for off-grid microgrids while long-term vision (5–10 years) shops green hydrogen seasonal storage, swarm intelligence for multi-station coordination, agrivoltaics integration.

The most critical near-term gap is the absence of field-validated optimization frameworks for off-grid hybrid EV charging. While TSDRO with Imprecise Dirichlet Models shows theoretical promise for data-scarce environments, empirical validation under real operating conditions—including Harmattan dust events, monsoon flooding, and extreme heat—remains essential. Comprehensive sizing algorithms incorporating high-resolution resource data, probabilistic EV demand models, and climate-specific degradation factors require development specifically for developing country deployment contexts [17–20].

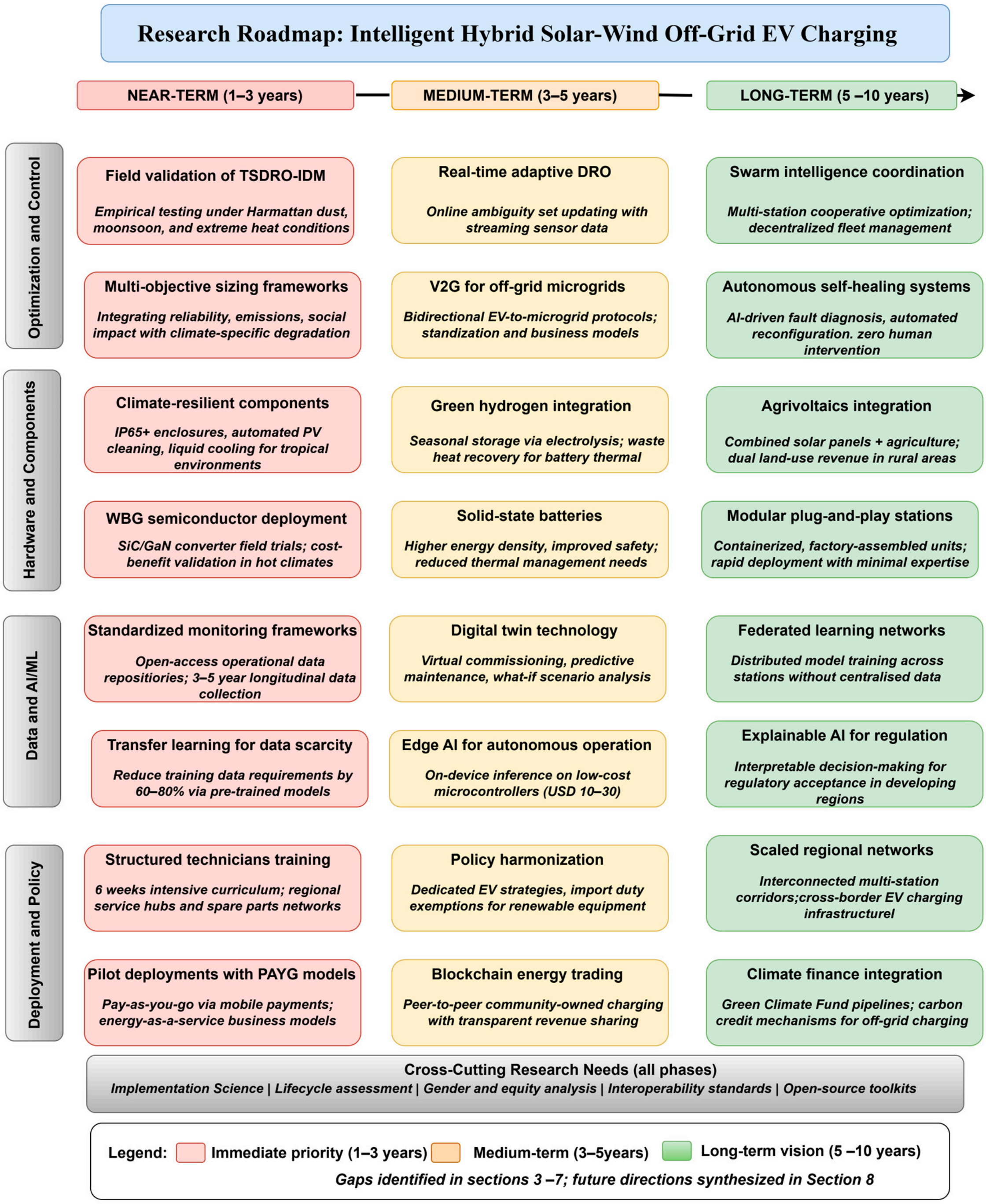

Figure 10. Research roadmap for intelligent hybrid solar–wind off-grid EV charging systems.

Emerging technologies present transformative opportunities. Digital twin technology enables virtual commissioning, predictive maintenance, and what-if analysis without disrupting physical systems [83]. Blockchain-based peer-to-peer energy trading could facilitate community-owned charging infrastructure with transparent revenue sharing [86]. Green hydrogen production via electrolysis provides seasonal energy storage addressing long-duration intermittency beyond battery capabilities [87]. Recent work on all-in-one EV station concepts demonstrates the feasibility of integrating battery charging, battery swapping, and hydrogen refueling within a single photovoltaic-supported facility [85], suggesting that future off-grid stations could evolve into multi-service energy hubs combining transportation electrification with hydrogen production for both mobility and stationary applications. V2G integration transforms EVs from passive loads to active microgrid resources, though standardization and business model challenges remain [88]. Recent advances in coupled electricity-transportation network resilience demonstrate the potential of electric buses and vehicles as mobile energy storage resources for decentralized load restoration, leveraging spatial-temporal flexibility and building thermal dynamics to ensure privacy-preserving recovery after extreme events [89]. These concepts are directly transferable to off-grid EV charging microgrids, where parked EVs could provide emergency backup power to critical community loads during extended renewable generation shortfalls. Edge computing with 5G/6G connectivity enables centralized fleet management while ensuring local autonomy during communication failures [90]. Agrivoltaics—combining solar panels with agricultural activities—optimizes land use and provides multiple revenue streams, particularly relevant for rural applications where land competition exists [91,92]. Finally, swarm intelligence approaches for coordinated multi-station operation warrant exploration as charging networks scale beyond individual installations [93]. Additionally, robust planning methodologies utilizing the inexact Column-and-Constraint Generation (I-C&CG) algorithm have demonstrated effectiveness in AC/DC hybrid distribution networks with EV demand response [94], providing complementary validation that the C&CG decomposition approach adopted in the TSDRO-IDM framework (Section 5.3) scales effectively to distribution-level planning problems incorporating EV flexibility.

Cross-cutting research needs include explainable AI for regulatory acceptance in developing country contexts, federated learning enabling model improvement across distributed stations without centralized data collection, and implementation science approaches documenting context assessment, adaptation processes, and scalability factors to build an evidence base for replication [5,14,23]. Two overarching priorities underpin all future research directions. First, scalability—transitioning from individual pilot stations to coordinated multi-station networks requires standardized modular architectures, regional service infrastructure, and interoperable monitoring platforms that have yet to be developed for off-grid developing country contexts. Second, long-term sustainability—the absence of operational data beyond 24 months means that lifecycle economics, component reliability under sustained harsh-climate operation, and the long-term viability of financing models remain unvalidated. Addressing these twin challenges is essential for translating the promising technical performance documented in this review into widespread, commercially sustainable deployment.

9. Conclusions

This systematic review synthesizes knowledge from 94 publications on intelligent hybrid solar–wind off-grid EV charging for developing regions, covering renewable integration, power electronics, energy storage, intelligent control, and deployment experience. Hybrid solar–wind systems demonstrate clear superiority over single-source alternatives, achieving 30–50% battery storage reductions, 15–25% lower LCOE (USD 0.08–0.15/kWh), capacity factors of 28–38%, and power continuity indices exceeding 0.93, driven by temporal complementarity between solar and wind resources. Wide-bandgap semiconductors enable 96–98% conversion efficiency, while LFP batteries with intelligent degradation-aware management provide 3000–5000 cycles with 20–30% lifetime extensions.

Among intelligent control strategies, the two-stage distributionally robust optimization framework with Imprecise Dirichlet Models emerges as particularly promising for developing country contexts, addressing the dual challenges of extreme uncertainty and data scarcity that render conventional stochastic and robust optimization approaches either unreliable or overly conservative. AI-enhanced hierarchical control incorporating reinforcement learning and deep neural networks improves system performance by 10–20% over conventional strategies, with emerging transfer learning and edge computing approaches enabling deployment on resource-constrained hardware.

However, the gap between theoretical promise and practical deployment remains substantial. Field validation is limited to short-term studies predominantly based on simulation; long-term operational data exceeding 24 months in harsh tropical conditions are virtually absent from the literature. Deployment experience from Nigeria and Kenya reveals that real-world operating costs routinely exceed projections by 2–3×, supply chain development requires 12–24 months, and local technical capacity building demands sustained investment. Realistic economic modelling incorporating degradation and losses yields LCOE estimates 39% higher than idealized assumptions, fundamentally affecting investment decisions.

Successful large-scale deployment requires coordinated action across four domains: technology development (field-validated optimization frameworks, climate-resilient components, edge AI), policy support (dedicated EV strategies, streamlined permitting, import duty exemptions for renewable equipment), innovative financing (pay-as-you-go, energy-as-a-service, public-private partnerships leveraging international climate finance), and human capital (structured technician training, regional service networks, longitudinal research partnerships for systematic knowledge accumulation). With appropriate support across these domains, intelligent hybrid solar–wind EV charging offers transformative potential for expanding clean transportation access in the regions that need it most.

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