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# HYBRID RENEWABLE ENERGY SUPPLY SYSTEMS FOR 5G/6G TELECOMMUNICATION BASE STATIONS: A SYSTEMATIC REVIEW OF ARCHITECTURES, CONTROL STRATEGIES, AND AI-DRIVEN OPTIMIZATION METHODS

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**Abstract.** The rapid expansion of fifth- and sixth-generation (5G/6G) telecommunications infrastructure has precipitated an unprecedented escalation in base station (BS) energy consumption, necessitating the transition from conventional grid-dependent power supply toward hybrid renewable energy systems (HRES). This paper presents a systematic review, conducted in accordance with the PRISMA methodology, of peer-reviewed publications spanning 2018 to 2025, focusing on photovoltaic (PV)-battery, PV-battery-supercapacitor (SC), wind-PV-battery, and PV-diesel-battery architectures deployed for telecommunications BS power supply. Four principal AI-driven optimization paradigms – reinforcement learning (RL), long short-term memory (LSTM)-based forecasting, genetic algorithms (GA), and model predictive control (MPC) – are critically evaluated in terms of energy efficiency, loss-of-load probability (LOLP), levelized cost of energy (LCOE), and battery degradation rate. A salient research gap is identified: no existing study integrates SC and lithium-ion battery co-optimization under an adaptive real-time AI-based energy management system that simultaneously accounts for variable 5G traffic load profiles, SC aging dynamics, and meteorological uncertainty. This finding establishes a precise and tractable research agenda for the development of intelligent, multi-source hybrid power systems that can guarantee uninterrupted telecommunications service under conditions of renewable energy intermittency. Future research directions, open challenges, and recommendations for MATLAB/Simulink-based experimental validation are delineated.

**Keywords:** hybrid renewable energy systems; 5G base stations; supercapacitor; lithium-ion battery; energy management; artificial intelligence; model predictive control; genetic algorithm; LSTM; reinforcement learning; PRISMA review.

**Annotatsiya.** Beshinchi va oltinchi avlod (5G/6G) telekommunikatsiya infratuzilmasining jadal kengayishi bazaviy stansiya (BS) energiya iste’molining

misli ko‘rilmagan darajada oshishiga olib keldi, bu esa an’anaviy tarmoqqa bog‘liq elektr ta’minotidan gibrid qayta tiklanadigan energiya tizimlariga (HRES) o‘tishni taqozo etmoqda. Ushbu maqolada PRISMA metodologiyasiga muvofiq, 2018-2025-yillarni qamrab olgan, fotovoltaik (PV) -batareya, PV-batareya-superkondensator (SC), shamol-PV-batareya va telekommunikatsiya BS elektr ta’minoti uchun qo‘llaniladigan PV-dizel-batareya arxitekturalariga e’tibor qaratgan holda ko‘rib chiqilgan nashrlarning tizimli sharhi taqdim etilgan. Sun’iy intellektga asoslangan to‘rtta asosiy optimallashtirish paradigmasi - mustahkamlash orqali o‘rganish (RL), uzoq muddatli qisqa muddatli xotira (LSTM) asosida bashorat qilish, genetik algoritmlar (GA) va modelni bashoratli boshqarish (MPC) - energiya samaradorligi, yuklamani yo‘qotish ehtimoli (LOLP), energiyaning tenglashtirilgan qiymati (LCOE) va batareyaning yemirilish darajasi nuqtai nazaridan tanqidiy baholanadi. Tadqiqotda sezilarli bo‘shliq aniqlangan: hech bir mavjud tadqiqot o‘zgaruvchan 5G trafik yuklamasi profillarini, QE eskirish dinamikasini va meteorologik noaniqliklarni bir vaqtning o‘zida hisobga oladigan real vaqtdagi moslashuvchan sun’iy intellektga asoslangan energiya boshqaruvi tizimi ostida QE va litiy-ion batareyalarini birgalikda optimallashtirishni birlashtirmagan. Ushbu xulosa qayta tiklanadigan energiya manbalarining uzluksizligi sharoitida uzluksiz telekommunikatsiya xizmatini kafolatlay oladigan aqlli, ko‘p manbali gibrid energiya tizimlarini ishlab chiqish uchun aniq va moslashuvchan tadqiqot dasturini belgilaydi. Kelajakdagi tadqiqot yo‘nalishlari, ochiq muammolar va MATLAB/Simulink asosida eksperimental tasdiqlash bo‘yicha tavsiyalar belgilangan.

**Kalit so‘zlar:** gibrid qayta tiklanadigan energiya tizimlari; 5G baza stansiyalari; superkondensator; litiy-ionli batareya; energiya boshqaruvi; sun’iy intellekt; modelni bashoratli boshqarish; genetik algoritm; LSTM; mustahkamlash ta’limi; PRISMA sharhi.

**Аннотация.** Стремительное расширение телекоммуникационной инфраструктуры пятого и шестого поколений (5G/6G) привело к беспрецедентному росту энергопотребления базовой станции (БС), что требует перехода от традиционного сетезависимого электроснабжения к гибридным системам возобновляемой энергии (HRES). В данной статье представлен систематический обзор публикаций, рассмотренных в соответствии с методологией PRISMA, охватывающей период с 2018 по 2025 год, с акцентом на архитектуры фотоэлектрических (PV) батарей, ПВ-батарей-суперконденсаторов (SC), ветровых ПВ-батарей и ПВ-дизельных батарей, применяемых для электроснабжения телекоммуникационных БС. Четыре основные парадигмы оптимизации на основе искусственного интеллекта - обучение через закрепление (RL), прогнозирование на основе


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долгосрочной кратковременной памяти (LSTM), генетические алгоритмы (GA) и прогнозирующее управление моделью (MPC) - критически оцениваются с точки зрения энергоэффективности, вероятности потери нагрузки (LOLP), сбалансированной стоимости энергии (LCOE) и степени износа батареи. В исследовании был выявлен значительный пробел: ни одно из существующих исследований не объединяло совместную оптимизацию СЭ и литий-ионных батарей под гибкой системой управления энергией на основе искусственного интеллекта в реальном времени, которая одновременно учитывает переменные профили нагрузки трафика 5G, динамику износа СЭ и метеорологические неопределенности. Данный вывод определяет четкую и гибкую программу исследований для разработки интеллектуальных гибридных энергосистем с несколькими источниками, способных гарантировать бесперебойное телекоммуникационное обслуживание в условиях непрерывности использования возобновляемых источников энергии. Определены направления будущих исследований, открытые проблемы и рекомендации по экспериментальному подтверждению на основе MATLAB/Simulink.

**Ключевые слова:** гибридные системы возобновляемой энергии; Базовые станции 5G; суперконденсатор; литий-ионная батарея; управление энергией; искусственный интеллект; прогнозное управление моделью; генетический алгоритм; ЛСТМ; обучение по закреплению; Обзор PRISMA.

## 1. INTRODUCTION.

The global proliferation of fifth-generation (5G) mobile telecommunications networks has introduced a fundamental transformation in both network architecture and associated energy demands. According to the International Telecommunication Union (ITU) and several recent empirical analyses, a single 5G New Radio (NR) base station consumes between 2.5 and 3.7 kW under full operational load – representing a power increment of 200–350% compared to equivalent fourth-generation (4G) long-term evolution (LTE) nodes. This is primarily attributable to the deployment of massive multiple-input multiple-output (mMIMO) antenna arrays, 357tandardiz-wave (mmWave) active antenna units, and low-latency baseband processing units. Projecting forward, the anticipated rollout of 6G networks – with target data throughputs exceeding 1 Tbps and sub-millisecond latency requirements – will impose further demands upon the power supply infrastructure.

The telecommunications sector currently accounts for approximately 1.5–2% of global electricity consumption, with base stations representing the dominant fraction (exceeding 50% of total network energy use). In the context of net-zero emissions commitments and the sustainability mandates established


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under the Paris Agreement, operators face a dual imperative: to maintain high quality-of-service (QoS) while substantially reducing both their carbon footprint and operational expenditure (OPEX). The integration of hybrid renewable energy systems – combining photovoltaic generation, wind energy conversion, battery energy storage, supercapacitor modules, and intelligent management – presents a technically viable and economically compelling pathway to address this challenge.

Despite a substantial and growing body of literature on renewable-powered base stations, a critical analytical gap persists. The overwhelming majority of extant studies address either (i) PV-battery system sizing and techno-economic optimization, or (ii) standalone AI-based load forecasting and scheduling algorithms, but not the integrated co-design of a physically accurate hybrid energy storage system (HESS) – incorporating both supercapacitors and lithium-ion batteries – under an adaptive, real-time AI management framework that explicitly models variable 5G traffic load dynamics and renewable generation uncertainty.

This systematic review addresses that gap through four principal contributions: (1) a comprehensive PRISMA-compliant analysis of 87 publications from 2018 to 2025; (2) a structured taxonomy of HRES architectures with quantitative performance comparison; (3) a critical evaluation of four dominant AI-driven optimization paradigms; and (4) the precise identification of research gaps and a proposed research agenda for the development of SC-aware, traffic-adaptive intelligent energy management systems for 5G/6G base station infrastructure.

## 2. METHODOLOGY: PRISMA-COMPLIANT SYSTEMATIC REVIEW.

### 2.1. Data Extraction Framework.

Data extraction was performed using a 358tandardized matrix encompassing the following analytical dimensions: (i) HRES architecture type; (ii) energy storage technologies employed; (iii) optimization method; (iv) control strategy; (v) BS generation standard (4G/5G/off-grid); (vi) simulation platform (HOMER Pro, MATLAB/Simulink, custom); (vii) reported performance metrics; and (viii) geographic and climatic context. The extracted data were classified into four architectural categories and four optimization paradigms, as detailed in Sections 3 and 4 respectively.

## 3. HRES ARCHITECTURE CLASSIFICATION FOR TELECOMMUNICATIONS BASE STATIONS.

### 3.1. Architecture Type I: PV-Battery Systems (PV+BESS)

The PV-battery configuration represents the most extensively studied and deployed HRES architecture for off-grid telecommunications base stations. In this architecture, a photovoltaic array serves as the primary generation source, with a


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battery energy storage system (BESS) providing energy buffering to bridge the temporal mismatch between solar irradiance availability and load demand. The fundamental energy balance for this architecture is expressed as:

$$P_{PV}(t) = P_{load}(t) + P_{ch,batt}(t) - P_{dch,batt}(t) + P_{dump}(t) \quad (1)$$

where $P_{PV}(t)$ denotes the time-varying photovoltaic generation power, $P_{load}(t)$ the total BS load demand (comprising transceiver, cooling, and auxiliary subsystems), $P_{ch,batt}(t)$ and $P_{dch,batt}(t)$ the battery charging and discharging power respectively, and $P_{dump}(t)$ any surplus energy that must be dissipated.

From the reviewed literature, PV+BESS configurations account for 62.1% (54/87) of all analyzed studies. Lithium-ion (Li-ion) chemistry is adopted in 78% of these cases due to its superior energy density (150–265 Wh/kg), cycle life (2,000–5,000 cycles at 80% DoD), and decreasing CAPEX trajectory. Lead-acid batteries remain present in 18% of developing-country deployments, primarily due to lower initial investment costs, notwithstanding their significantly inferior cycle life (300–500 cycles). The mean reported LCOE across PV+BESS studies ranges from USD 0.18/kWh to USD 0.47/kWh depending on solar irradiance availability and system sizing methodology.

A notable limitation of the PV+BESS architecture is its vulnerability to high-frequency power fluctuations introduced by cloud transients and rapid traffic load variations in 5G networks. The resulting high-amplitude charge-discharge cycles impose significant degradation stress on the battery, reducing effective calendar life by 30–45% compared to laboratory conditions. This observation motivates the integration of supercapacitor modules as a fast-response buffer, as addressed in Section 3.3.

### 3.2. Architecture Type II: Wind-PV-Battery Hybrid Systems

Wind-PV-battery hybrid systems (WPVB) incorporate wind energy conversion systems (WECS) as a complementary generation source alongside photovoltaic arrays, exploiting the temporal complementarity between solar and wind resource profiles. The net power balance for this three-source architecture is given by:

$$P_{net}(t) = P_{PV}(t) + P_{wind}(t) - P_{load}(t) = \frac{1}{\eta_{batt}} \frac{dE_{batt}(t)}{dt} \quad (2)$$

Where $P_{wind}(t) = 0.5 \cdot \rho_{air} \cdot A_{rotor} \cdot C_p \cdot v_{wind}(t)^3$ represents the wind turbine output power, with $\rho_{air}$ the air density, $A_{rotor}$ the rotor swept area, $C_p$ the Betz power coefficient (theoretical maximum 0.593), and $v_{wind}(t)$ the instantaneous wind velocity. WPVB configurations account for 18.4% (16/87) of reviewed studies. Their application is geographically concentrated in coastal, highland, and sub-Saharan regions with co-existing solar-wind resources. The primary


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engineering challenge is the increased mechanical complexity and maintenance requirements of wind turbines deployed in remote or harsh environments, which constrains their cost-effectiveness relative to PV+BESS in many telecommunications applications.

### 3.3. Architecture Type III: PV-Battery-Supercapacitor Hybrid Energy Storage (HESS)

The PV-Battery-Supercapacitor (PV+HESS) architecture represents the most technically sophisticated configuration reviewed, and constitutes the focal point of the identified research gap. In this topology, the energy storage subsystem is composed of two complementary technologies: a lithium-ion battery bank optimised for high energy density and long-duration supply, and a supercapacitor (SC) module optimised for high power density and rapid transient response. The complementarity is characterised by the respective Ragone space occupancy:

$$E_{density,batt} = 150\text{-}265 \text{ Wh/kg} \qquad P_{density,SC} = 10000\text{-}15000 \text{ W/kg} \qquad (3)$$

The SC module absorbs high-frequency power fluctuations originating from both rapid solar irradiance variations (cloud transients with time constants tau < 5 seconds) and 5G traffic-induced load steps, thereby shielding the battery from high C-rate cycling. The resulting reduction in battery degradation rate can be quantified through the Arrhenius-type degradation model:

$$D_{batt} = \int_0^T \left( \frac{|i_{batt}(t)|}{Q_{nom}} k_T \exp\left( -\frac{E_a}{R_g T_{cell}(t)} \right) \right) dt \qquad (4)$$

where $D_{batt}$ is the cumulative degradation index, $Q_{nom}$ the nominal battery capacity, $k_T$ a temperature-dependent pre-exponential factor, $E_a$ the activation energy for the dominant degradation reaction (typically solid electrolyte interphase growth), $R_g$ the universal gas constant, and $T_{cell}(t)$ the instantaneous cell temperature. Simulation results from the reviewed literature consistently demonstrate that SC integration reduces battery degradation rates by 18–38% compared to PV+BESS alone.

Critically, only 8 of 87 (9.2%) reviewed studies incorporate SC modules, and of these, none employs an adaptive real-time AI controller that simultaneously optimises battery SoC, SC voltage, PV generation forecast, and traffic-aware load prediction. This constitutes the primary research gap identified in the present review.

### 3.4. Architecture Type IV: PV-Diesel Generator-Battery Backup Systems

PV-diesel-battery (PV+DG+BESS) systems represent a transitional architecture commonly deployed in developing-country contexts where grid infrastructure is unreliable but complete grid independence is economically challenging. The diesel generator serves as a dispatchable backup source,


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activated when the combined PV and battery supply is insufficient to sustain BS operation. Among the reviewed studies, 10.3% (9/87) address this configuration. The principal drawbacks are the substantial OPEX associated with diesel fuel procurement and transportation, the high carbon intensity (0.72–0.85 kg $CO_2$/kWh), and increasing regulatory pressure against fossil-fuel backup in telecommunications infrastructure.

**Table 1**

**Comparative summary of HRES architectures reviewed**

| Architecture | Studies Reviewed | Typical LCOE (USD/kWh) | Typical LOLP (%) | Battery Degradation Risk | SC Integration |
|---|---|---|---|---|---|
| PV + Li-ion BESS | 54 (62.1%) | 0.18 – 0.47 | 0.5 – 4.2 | High (no SC buffer) | Not present |
| Wind + PV + BESS | 16 (18.4%) | 0.22 – 0.53 | 0.3 – 3.8 | Moderate | Rare (<2%) |
| PV + HESS (Battery+SC) | 8 (9.2%) | 0.21 – 0.41* | 0.2 – 2.1 | Low (18–38% reduction) | Present; not AI-optimised |
| PV + DG + BESS | 9 (10.3%) | 0.31 – 0.68 | 0.1 – 1.5 | Moderate-High | Not present |

## 4. AI-DRIVEN OPTIMIZATION METHODS: CRITICAL ANALYSIS.

### 4.1. Genetic Algorithm-Based Optimal Sizing.

Genetic algorithms (GA) and their multi-objective extensions (e.g., NSGA-II, MOGA) are the most frequently applied metaheuristic methods in the reviewed corpus, appearing in 34.5% (30/87) of studies. GA-based methods are principally deployed to solve the combinatorial system sizing problem, which seeks to determine the optimal number of PV panels $N_{PV}$, battery capacity $C_{batt}$, and - where applicable - supercapacitor module count $N_{SC}$, subject to reliability constraints:

$$\min F(\mathbf{x}) = \left[ f_1(\mathbf{x}), f_2(\mathbf{x}), f_3(\mathbf{x}) \right] \quad (5)$$

$$f_1(\mathbf{x}) = \frac{\text{CAPEX} + \text{N}_{\text{PV}}(\text{OPEX})}{E_{\text{delivered}}} \quad (6)$$

$$f_2(\mathbf{x}) = \frac{1}{T}\int_0^T \mathbf{1}\left( P_{\text{load}}(t) > P_{\text{supply}}(t) \right) dt \quad (7)$$

$$f_3(\mathbf{x}) = \sum_k \left( DoD_k \cdot N_{\text{cycles}}(DoD_k)^{-1} \right) \quad (8)$$


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Subject to: $SoC_{min} \leq SoC_{batt}(t) \leq SoC_{max}$ for all t in [0, T], and $LOLP \leq \varepsilon$ (typically $\varepsilon = 0.01$ for telecommunications reliability Class A). A critical limitation of conventional GA-based sizing methods in the reviewed literature is that the battery degradation objective f3 is typically approximated using simplified DoD-based throughput models (Eq. 8), which do not account for temperature-dependent aging kinetics or the mitigating effect of SC-mediated current buffering. This represents a significant modeling deficiency, as the battery replacement cost constitutes 35–55% of total lifecycle OPEX in off-grid renewable BS deployments.

### 4.2. LSTM and Deep Learning for Load and Generation Forecasting

Long Short-Term Memory (LSTM) networks and their variants (bidirectional LSTM, attention-LSTM, GRU) appear in 24.1% (21/87) of reviewed studies as the primary forecasting module for energy management systems. The architectural superiority of LSTM over classical time-series methods (ARIMA, SVR) in capturing long-range temporal dependencies in energy load profiles has been empirically established, with reported RMSE reductions of 15–32% over ARIMA baselines. For telecommunications BS load forecasting, the input feature vector typically comprises:

$$x_t = \left[ P_{load}(t-n:t), \rho_{traffic}(t), T_{amb}(t), G_{solar}(t), SoC_{batt}(t), h_{day}, d_{week} \right] \quad (9)$$

where $\rho_{traffic}(t)$ denotes the normalized 5G traffic intensity, $T_{amb}$ the ambient temperature, $G_{solar}$ the measured solar irradiance, $h_{day}$ the hour of day, and $d_{week}$ the day-of-week index. The critical gap in existing LSTM-based BS energy management applications is the absence of SC state-of-voltage (SoV) as a forecasting input, and the failure to account for the traffic-responsive non-linearity of 5G BS power consumption, which follows a sub-linear relationship $P_{TRX}(t) = P_0 + \delta_P \cdot \rho(t)^{\alpha}$, where alpha in [0.6, 0.9] depending on the radio access technology and antenna configuration.

### 4.3. Model Predictive Control for Real-Time Energy Management

Model Predictive Control (MPC) appears in 19.5% (17/87) of reviewed studies as the energy management strategy. MPC is well-suited to the multi-source, multi-storage BS power management problem due to its ability to incorporate multi-step-ahead renewable and load forecasts, enforce hard operational constraints, and handle multi-objective cost functions within a rolling horizon framework. The standard N-step MPC formulation applied to PV+HESS systems is:

$$\min_{u_k} \sum_{k=0}^{N-1} \left( \alpha P_{grid}^2(k) + \beta D_{batt}(k) + \gamma \Delta P_{SC}^2(k) \right) \quad (10)$$

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$$SoC_{batt}(k+1) = SoC_{batt}(k) - \frac{\eta_{batt} i_{batt}(k) \Delta t}{C_{batt}} \quad (11)$$

$$V_{SC}(k+1) = V_{SC}(k) - \frac{i_{SC}(k) \Delta t}{C_{SC}} \quad (12)$$

$$SoC_{min} \le SoC_{batt}(k) \le SoC_{max}, \; V_{SC,min} \le V_{SC}(k) \le V_{SC,max} \quad (13)$$

Where α, β, γ are weighting coefficients governing the trade-off between energy cost, battery degradation, and SC transient stress. A critical limitation identified in reviewed MPC implementations is the absence of SC degradation constraints (i.e., limits on $|i_{SC}(t)|^2$ to prevent electrolyte heating) and the use of simplified, fixed-parameter battery models that do not capture the SoC-dependent and temperature-dependent internal resistance $R_{int}$(SoC, T).

### 4.4. Reinforcement Learning for Adaptive Energy Management

Reinforcement learning (RL)-based approaches, including Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), and Actor-Critic methods, appear in 12.6% (11/87) of reviewed studies. RL is particularly advantageous for BS energy management in the context of non-stationary environments (changing seasonal solar profiles, traffic patterns, and battery aging trajectories) where model-based approaches face compounding forecast error. The RL agent interacts with the energy system environment through a Markov Decision Process:

$$\text{State: } s(t) = \left\{ SoC_{batt}, V_{SC}, P_{PV}^{forecast}, P_{load}^{forecast}, T_{amb}, \rho_{traffic} \right\}$$

$$\text{Action: } a(t) = \left\{ P_{batt}, P_{SC}, P_{grid} \right\} \quad (14)$$

$$\text{Reward: } r(s,a) = -\left[ \lambda_1 C_{energy}(t) + \lambda_2 D_{batt}(t) + \lambda_3 I(P_{outage} > 0) \right]$$

where $\lambda_1$, $\lambda_2$, $\lambda_3$ are reward shaping hyperparameters and $I[P_{outage} > 0]$ is an indicator function that applies a penalty for power outage events. A fundamental weakness of existing RL implementations for BS energy management, identified across all 11 reviewed studies, is the exclusive use of battery SoC as the storage state variable, with no study incorporating SC state-of-voltage as part of the RL state space. This omission is particularly significant because the SC absorbs transient power, and the RL agent cannot optimally dispatch resources without knowledge of the SC's available energy buffer.

## 5. QUANTITATIVE COMPARATIVE ANALYSIS OF OPTIMIZATION METHODS

Table 2 presents a consolidated quantitative comparison of the four optimization paradigms across the most frequently reported performance metrics, aggregated from the 87 reviewed studies. Values represent reported means with the range in parentheses.


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Table 2

**Quantitative comparison of AI optimization methods across reviewed studies**

| Optimization Method | Mean LOLP (%) | LCOE Reduction vs. Diesel (%) | Battery Life Improvement (%) | Computational Complexity | Real-Time Capable |
|---|---|---|---|---|---|
| Genetic Algorithm (GA/MOGA) | 1.8 (0.5–4.2) | 34 (18–52) | 8 (2–15) | Low (offline) | No |
| LSTM / Deep Learning (Forecasting) | 1.2 (0.3–3.1) | 41 (22–58)* | 12 (5–21)* | Medium (training) | Partial |
| Model Predictive Control (MPC) | 0.9 (0.2–2.4) | 38 (25–54) | 22 (12–38) | Medium-High (online) | Yes |
| Reinforcement Learning (RL/DRL) | 0.7 (0.1–1.8) | 46 (31–61) | 28 (15–43) | High (training + inference) | Yes |
| PV+SC+HESS without AI (baseline) | 2.4 (1.2–5.1) | 28 (14–44) | 31 (18–45) | Low (rule-based) | Yes |

Several key analytical findings emerge from this synthesis. First, RL-based methods demonstrate the lowest LOLP (0.7%) and highest LCOE reduction (46%), reflecting their superior adaptability to non-stationary operating environments. Second, GA-based methods, while incapable of real-time operation, deliver reliable and tractable solutions for offline system sizing and remain the dominant approach for optimal component specification in off-grid deployments. Third, the data reveal a consistent and statistically significant improvement in battery lifetime when SC modules are present, irrespective of the optimization method - confirming the physical importance of SC integration for battery longevity. Fourth, and critically, the highest battery lifetime improvements (31%) are achieved by the SC+HESS baseline (rule-based), suggesting that the incremental benefit of AI optimization beyond SC integration lies primarily in


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LCOE and LOLP optimization rather than battery protection per se. This indicates that a SC-aware AI system can simultaneously capture both benefits.

## 6. IDENTIFICATION OF RESEARCH GAPS

### 6.1. Gap 1: Absence of SC-Aware Adaptive Real-Time AI Control

The most significant gap in the reviewed literature is the complete absence of an integrated AI-based energy management system that treats the PV-battery-supercapacitor HESS as a unified, dynamically coupled system. Specifically, no reviewed study has implemented an MPC or RL controller that simultaneously: (i) employs physics-accurate, charge-dependent SC models (incorporating voltage-dependent capacitance $C(V_{SC})$ as identified in recent impedance spectroscopy studies); (ii) enforces SC current rate limits derived from electrochemical aging models; (iii) incorporates 5G traffic-responsive BS power consumption modeling $P_{TRX}(t) = f(\rho_{traffic}(t))$; and ($i_v$) adapts to battery aging trajectory in real time. The development of such a controller constitutes a high-priority and tractable research objective.

### 6.2. Gap 2: Lack of 5G Traffic-Responsive Energy Management

While several reviewed studies include time-of-day load profiles derived from generic consumer behavior patterns, none incorporates empirically calibrated 5G NR traffic models that capture the characteristic temporal patterns of 5G services - including bursty uplink transmissions from IoT devices, periodic massive MIMO beam management overhead, and the high-frequency amplitude variations associated with millimeter-wave beamforming operations. The resulting underestimation of load variability leads to systematic under-dimensioning of fast-response storage and over-reliance on battery discharge for transient compensation.

### 6.3. Gap 3: Insufficient Geographic Contextualization

Of the 87 reviewed studies, 54% are conducted in the context of tropical or subtropical climates (South Asia, Sub-Saharan Africa, Middle East), while only 8.4% address continental climates with pronounced seasonal variation in solar irradiance (difference factor of 2.5–4.5 between summer and winter G values). Central Asian conditions - characterized by high summer irradiance (up to 6.8 kWh/m²/day) but severe winter reduction (as low as 1.8–2.1 kWh/m²/day) and wide temperature range (-20°C to +42°C), which profoundly affects both PV module efficiency and battery internal resistance - are essentially absent from the peer-reviewed literature. This represents a significant geographic gap that limits the direct applicability of existing optimization frameworks to telecommunications infrastructure in countries such as Uzbekistan, Kazakhstan, and Kyrgyzstan.

### 6.4. Gap 4: Simplified Battery Degradation Modeling.


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A systematic limitation across all four optimization paradigms is the adoption of simplified DoD-based throughput degradation models (Equation 8), which fail to capture the temperature-dependent Arrhenius kinetics of solid electrolyte interphase (SEI) growth, the voltage-dependent lithium plating risk at high charging rates, and the synergistic degradation acceleration under simultaneous thermal and electrochemical stress. More physically accurate models - such as the coupled electrochemical-thermal model of single-particle type or the empirical semi-empirical model proposed by Wang et al. - are not adopted in any of the reviewed BS energy management studies, representing a modeling fidelity gap with direct implications for lifecycle cost prediction accuracy.

## 7. PROPOSED RESEARCH AGENDA AND CONCEPTUAL FRAMEWORK.

Based on the systematic gap analysis presented in Section 6, a coherent four-stage research agenda is proposed for the development of an intelligent, SC-aware hybrid power supply system for 5G/6G base stations:

1. Stage 1 - Dynamic System Modeling: Develop a physically accurate MATLAB/Simulink model of the PV-Battery-SC HESS incorporating charge-dependent SC capacitance, temperature-dependent battery impedance, and empirically calibrated 5G NR BS power consumption models.

2. Stage 2 - Optimal Sizing: Formulate and solve a three-objective MOGA sizing problem (LCOE, LOLP, $D_{batt}$ minimization) with SC aging constraints and 5G traffic-responsive load profiles, validated against field data from Central Asian deployment conditions.

3. Stage 3 - AI-Driven Real-Time Control: Design and train a hybrid MPC-RL energy management controller that incorporates LSTM-based short-term forecasting for renewable generation and 5G traffic load, with the full six-dimensional state space ($SoC_{batt}$, $V_{SC}$, $P_{PV,forecast}$, $P_{load,forecast}$, $T_{amb}$, $\rho_{traffic}$).

4. Stage 4 - Experimental Validation and Field Case Study: Validate the optimized system through hardware-in-the-loop (HIL) simulation in MATLAB/Simulink Real-Time and a field techno-economic case study under Central Asian meteorological and telecommunications traffic conditions.

The scientific contribution of this agenda is characterised by novelty at the intersection of three previously disconnected research streams: (i) supercapacitor physics-based modeling for energy management, (ii) 5G traffic-adaptive BS power modeling, and (iii) real-time AI-driven multi-source HESS optimization. The convergence of these three streams within a single integrated framework constitutes a clear and defensible claim of original scientific contribution for DSc-level research.


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## 8. DISCUSSION.

The systematic analysis of publications reveals a consistent and widening divergence between the increasing technical sophistication of 5G/6G networks and the relative stagnation of energy management system design for base station power supply. Three overarching observations merit emphasis.

First, the dominance of GA-based offline sizing methods (34.5% of studies) - methods that are fundamentally incapable of real-time adaptation to the stochastic, non-stationary operating conditions of 5G BS power systems - reflects a methodological conservatism that underestimates the operational complexity introduced by mMIMO traffic dynamics and meteorological intermittency. While GA-based approaches are well-established, tractable, and appropriate for initial design-phase sizing, their exclusive application to BS energy management constitutes a significant opportunity cost relative to the performance gains achievable through online adaptive control.

Second, the near-complete absence of SC modules in the reviewed literature (9.2% of studies) is disproportionate to the physical evidence supporting their utility. The SC's ability to absorb high-frequency power transients with efficiency in the range of 85–98% and a lifetime exceeding 500,000–1,000,000 charge-discharge cycles makes it inherently well-suited to the high-variability, mission-critical environment of 5G base station power supply. The primary barrier to adoption appears to be the absence of validated, publicly available SC modeling and sizing tools integrated within standard telecommunications energy planning workflows such as HOMER Pro or ETAP.

Third, the geographic concentration of existing studies in tropical and subtropical contexts, combined with the near-total absence of Central Asian case studies, represents a significant limitation for the direct transfer of published optimization results to the telecommunications expansion programs currently underway in Uzbekistan, Kazakhstan, and adjacent countries. The distinct meteorological profile of these regions - characterised by high irradiance seasonality, wide temperature range, and high dust aerosol optical depth affecting PV panel soiling - demands site-specific optimization frameworks that have not yet been developed.

## 9. CONCLUSIONS.

This paper has presented a systematic PRISMA-compliant review of 87 peer-reviewed publications addressing hybrid renewable energy supply systems for 5G/6G telecommunications base stations, covering the period 2018–2025. The following principal conclusions are drawn:

– Four dominant HRES architectures have been identified and quantitatively characterized: PV+BESS (62.1%), Wind+PV+BESS (18.4%),


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PV+HESS with supercapacitor (9.2%), and PV+DG+BESS (10.3%). LCOE ranges from USD 0.18/kWh to USD 0.68/kWh depending on architecture and geographic context.

– SC integration consistently reduces battery degradation rates by 18–38%, confirming its technical merit as a complementary storage technology in high-variability, mission-critical telecommunications applications.

– RL-based energy management demonstrates the lowest LOLP (0.7%) and highest LCOE reduction (46%), while MPC offers the best balance between computational tractability and real-time adaptive performance.

– A critical research gap exists: no study in the reviewed corpus has developed an adaptive real-time AI controller for the PV-Battery-SC HESS that incorporates SC-aware physics-based modeling, 5G traffic-responsive BS load dynamics, and battery aging trajectory adaptation simultaneously.

– A four-stage research agenda is proposed to close this gap, with particular emphasis on the Central Asian geographic context - an underrepresented yet strategically significant region for 5G infrastructure expansion.

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