Review and Future Directions for Distributed Energy Systems in Emerging Economies

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INTRODUCTION

Exploring renewable energy in accordance by sustainable development goal (SDG) 7 could improve the insufficient and instability of energy which is caused by chronic underinvestment, large transmission losses, and deep operational instability (Pepermans et al., 2005; Taneja, 2019; Blimpo & Cosgrove-Davies, 2019). Nigeria has undertaken various reforms in the power sector, yet the challenges of generation shortfalls and transmission bottlenecks continue to limit electricity supply across the country.

PROBLEM STATEMENT

Despite the growing deployment of Distributed Energy Systems (DES) in emerging economies, existing planning and optimization models remain fragmented across engineering, economic, and socio-regulatory dimensions, limiting their effectiveness for real-world deployment.

AIM AND OBJECTIVES

This review aims to provide a comprehensive and critical synthesis of DES modeling, moving beyond a component-by-component review to interrogate the integration gaps that impede scalable implementation.

To achieve this, the following are the objectives :

1. Document the history of DES modeling from deterministic engineering to AI-driven digital twins;
2. Analyze the representative studies from Engineering to digitalization of DES and identifying the gaps; and
3. Provide a HIM (Holistic Integrated Modelling) framework aimed at actionable outcomes for sub-national grid autonomy.

LITERATURE REVIEW

Table 1: Comparative literature matrix highlighting modelling choices and limitations relevant to deployable DES scale-up. Adapted from Lasseter (2018) and Rahman and Hossain (2020).

Study/Strand	Technical model	Economic model	Risk/uncertainty treatment	Socio-regulatory treatment	Key limitation for scale-up
HOMER-style hybrid sizing (Olorukooba, H. O et al., 2006; Díaz et al., 2008)]	Steady-state sizing; reliability proxies (e.g., unmet load)	NPC/LCOE minimization	Typically deterministic; sensitivity analysis	Usually none; assumes permits/tariffs given	Ignores stability, interoperability, and institutional friction
Two-stage stochastic DES planning (Hassan et al., 2022; Lee et al., 2023)	Power balance + operational constraints	Expected operating cost + CAPEX	Scenario-based stochastic programming	Often omitted or qualitative	Scenario realism and regulatory delays rarely modelled; computational burden
Robust optimization for resilience (Akbari et al., 2021)	Feasibility under uncertainty set Ω	Min–max cost or constraint violations	Worst-case (set-based) uncertainty	Rarely explicit	Conservatism can inflate costs; weak linkage to adoption/permits
Digital twins for operation and maintenance (Rahman & Hossain, 2020; Kumar & Zhang, 2023)	Cyber-physical model + data assimilation	Maintenance/availability impacts	Forecast error and model mismatch	Cybersecurity sometimes included (Khan et al., 2020)	Data/ICT readiness and standards compliance often under-specified
Regulatory sandbox mini-grid studies (Aghetuyi et al., 2018; Wu et al., 2017)	Often descriptive; limited technical constraints	Tariff and cost-recovery framing	Policy uncertainty discussed	Central focus (licensing, tariffs)	Limited integration into unified optimization; weak coupling to stability constraints

METHODOLOGY AND ANALYTICAL FRAMEWORK

This study aims to enhance such insights by attempting to develop a formal and quantifiable index of energy autonomy, as per the characterization given in Equation (1).

$$E = f(T, R, P, D, S) \quad (1)$$

Where:

T = Technological Innovation (inverters, BESS, IoT)

R = Regulatory Frameworks (Licensing, Tariffs, Grid codes)

S = Socio-Technical Acceptance (Community engagement, Local skills)

P = price trends (PV/BESS cost declines)

D = Digitalization (SCADA, AI, Cloud analytics)

Evolution of DES Modelling: From Deterministic to Digital

Most fundamentally, Distributed Energy Systems (DES) can be characterized by equation 2, given as:

$$P_g(t) \pm P_b(t) \pm P_{grid}(t) = P_l(t) + P_{loss}(t) \qquad (2)$$

local sources (P_g), the battery storage systems (P_b), and the energy exchanged with the primary grid (P_{grid}), the consumer demand (P_l), the electrical losses (P_{loss})

Evolution of DES Modelling: From Deterministic to Digital

Phase I (1990–2005): Stand-Alone Systems

The first versions of DES were mainly made of stand-alone configurations including basic solar home systems (SHS) and pico-hydro systems (ISLAND) (Paish, 2002; Martinot et al., 2002).

Evolution of DES Modelling: From Deterministic to Digital

Phase II (2005–2015): Hybrid Optimization Systems

The period defined by the use of specialized optimization tools, especially HOMER (Lambert et al., 2006), The almost universal objective was to minimize cost:

$$Z = C_{capex} + C_{oper} + C_{fuel} + C_{maint} \quad (3)$$

(C_{capex}), recurrent operational costs (C_{oper}), fuel costs (C_{fuel}) and maintenance needs (C_{maint}) make up the total system cost (Z).

Evolution of DES Modelling: From Deterministic to Digital

Phase III (2015–Present): Smart Digitalized Microgrids

We are already in a phase where deep digital integration characterizes Distributed Energy Systems (DES). Current systems combine the Internet of Things (IoT), advanced power electronics, and Artificial Intelligence (AI)-based prediction to optimize the management of energy flows (Rahman & Hossain, 2020).

$$A = \frac{E_{local}}{E_{demand}} \times 100\% \qquad (4)$$

Evolution of DES Modelling: From Deterministic to Digital

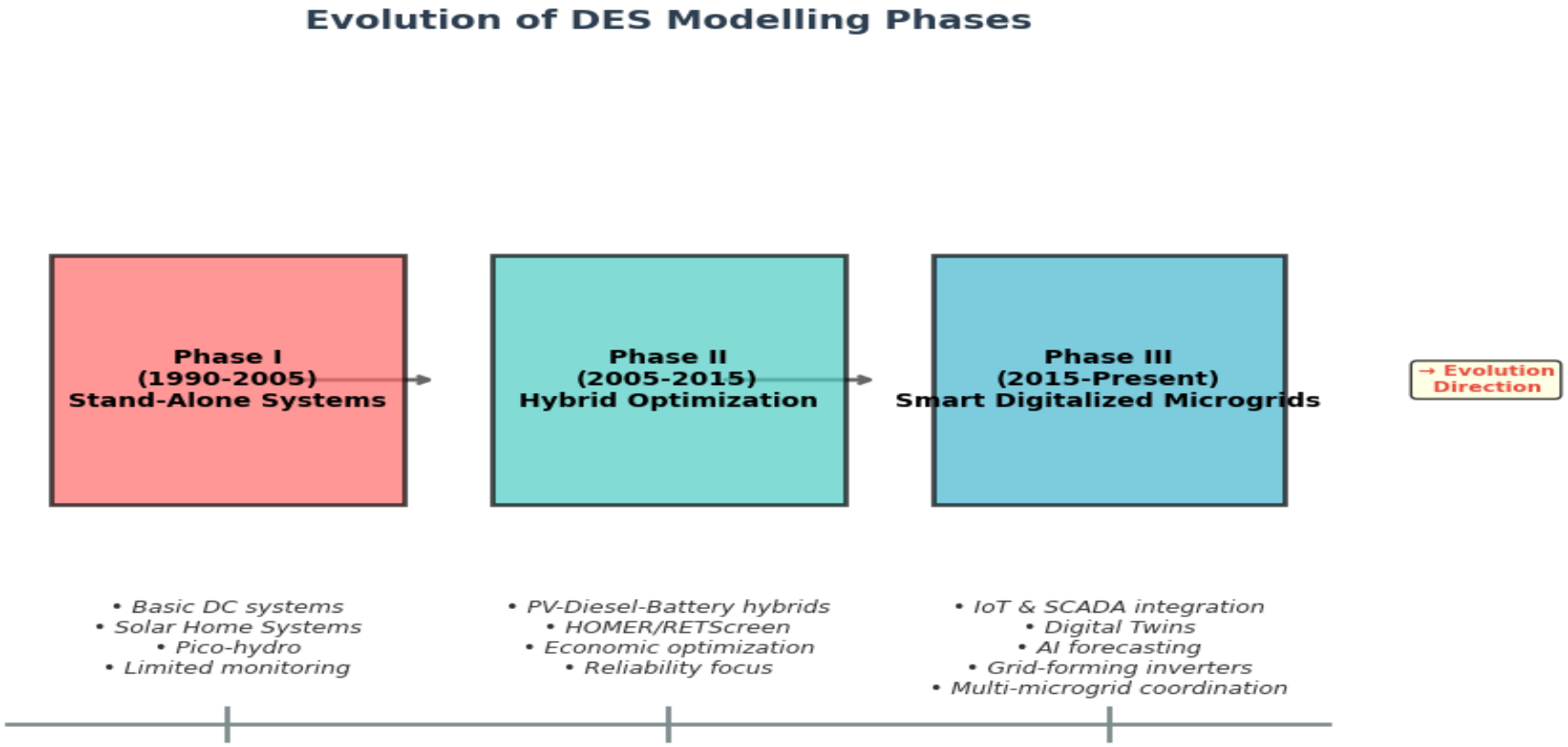


Figure 1: Evolution of DES modelling phases: from stand-alone systems to smart digitalized microgrids. Adapted from Lasseter (2018) and Rahman and Hossain (2020).

Engineering and Deterministic Foundations

Load and Generation Models

Load profiles are typically represented as time-series (Bonsu et al., 2023; Rabiu et al., 2024) with total electrical load $L(t)$ (demand) at time *t*, Base load L_{base} the minimum, steady, non-varying component of demand like lighting and essential equipment and Time-varying component $L_{var}(t)$ of the load profile caused by daily patterns, appliances, weather, or customer behavior.

$$L(t) = L_{base} + L_{var}(t) \tag{5}$$

Engineering and Deterministic Foundations

LOAD AND GENERATION MODELS

PV output power ($P_{PV}(t)$) depends on the solar irradiance (G(t)), the effective PV module area or installed capacity (A), and the PV conversion efficiency (η_{PV}). The temperature coefficient (γ) and the cell temperature (TC) deviation from the standard test condition reference of ($25°C$) capture the impacts of temperature

$$P_{PV}(t) = G(t) \,.\, A \,.\, \eta_{PV} \,.(1 - \gamma(T_C - 25^{O}C)) \qquad (6)$$

Engineering and Deterministic Foundations

Battery and Generator Models

Energy storage, described as the 'metabolic' center of a DES, its center of charge (SOC) behavior, plays a pivotal role (Wong et al., 2024; Zhang et al., 2023). This transition is captured by the following temporal logic:

$$soc(t+1) = SOC(t) + \left[P_{bc}(t).\eta_c - \frac{P_{bd}(t)}{\eta_d}\right] \quad (7)$$

Engineering and Deterministic Foundations

Techno-Economic Metrics

The techno-economic metrics act as the primary filter for establishing whether a DES configuration is likely to transition from a theoretical model to a fundable project (IEA, 2023; Adeoye et al., 2024).

$$LCOE = \frac{\sum_{t=1}^{N} \frac{C_t}{(1+r)^t}}{\sum_{t=1}^{N} \frac{E_t}{(1+r)^t}} \quad (8)$$

Future Directions of DES

Two-Stage Stochastic Programming

A common strategy to address this uncertainty is using the Two-Stage Stochastic Programming approach (Zhao et al., 2022; Wang et al., 2023). This method effectively separates "here-and-now" decisions from "wait-and-see" operational adjustments:

$$Z = C(x) + E_{\omega}[Q(x, \omega)] \quad (9)$$

$$Q(x, \omega) = min\, O(y, \omega) \quad (10)$$

Future Directions of DES

Robust Optimization: Worst-case guarantee perspective

While stochastic programming deals with the "expected" or average outcome, some of the resilience-critical applications, such as autonomous sub-national grids, require a more prudent approach. Robust optimization aims to shield the system from the worst possible outcomes concerning uncertainty (Akbari et al., 2021):

$$\min_{x} \max_{\omega \in \Omega} C(x, \omega) \qquad (11)$$

Future Directions of DES

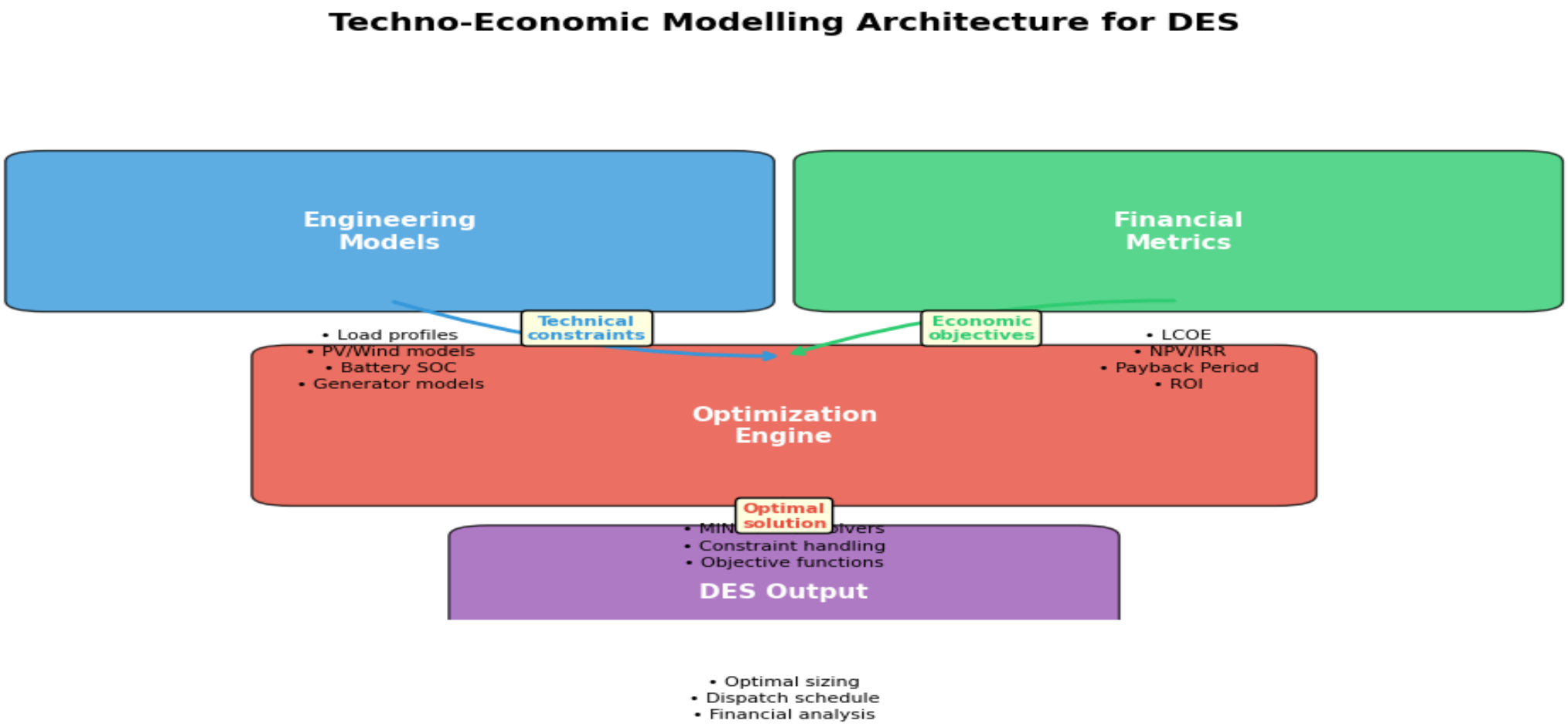


Figure 2: Techno-economic modelling architecture for DES, integrating engineering and financial metrics. Adapted from Adeoye and Akinyele (2024) and Blanco et al. (2012).

Future Directions of DES

Scenario Generation and statistical fidelity

The construction of the scenarios themselves is perhaps the most important aspect of any uncertainty-aware model. Typically, researchers derive these potential worlds using moment matching, a clustering approach, or sampling based on copulas (Hassan et al., 2022):

$$\omega = g(\mu, \sigma, \rho) \tag{12}$$

Future Directions of DES

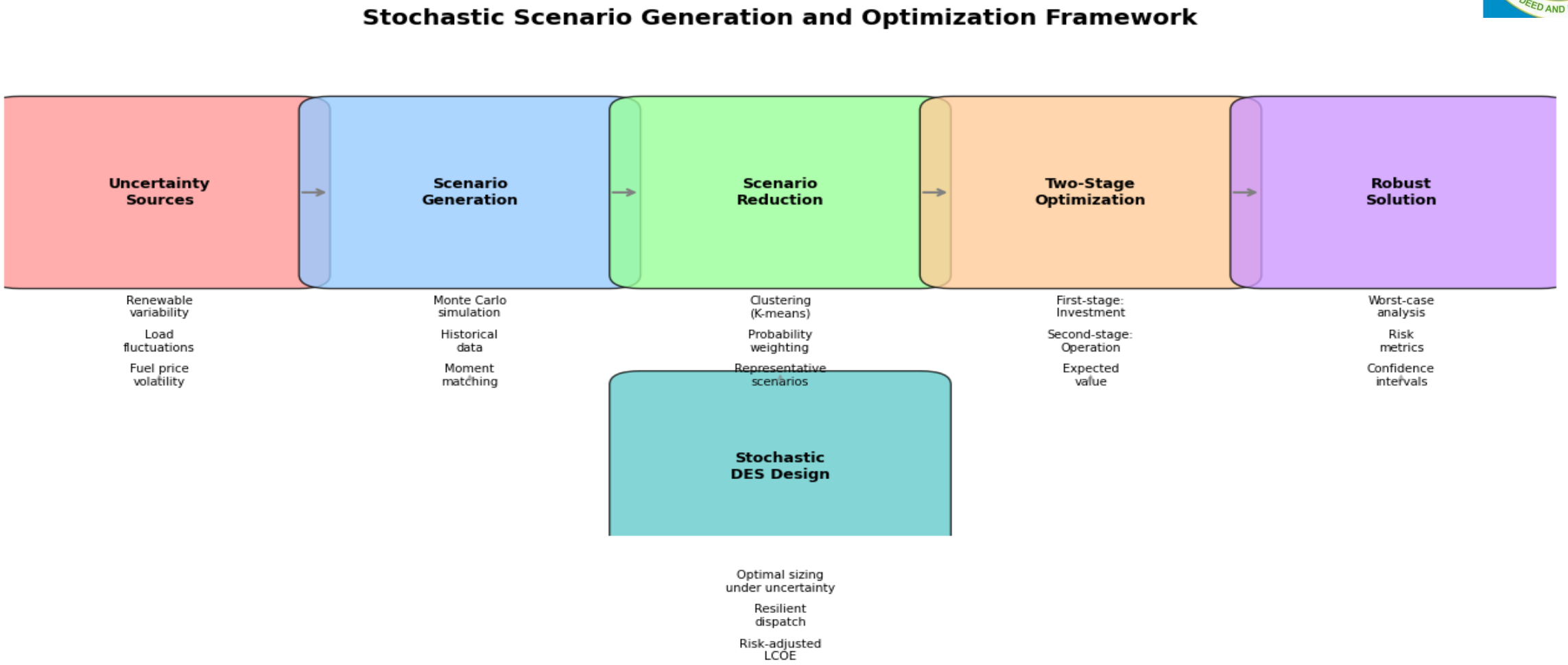


Figure 3: Stochastic scenario generation and optimization framework for DES under uncertainty. Adapted from (Hassan et al., 2022; Lee et al., 2023).

Digital Twins and Cybersecurity

Digital Twin Architecture

Digital Twins (DT) are the most advanced form of DES digitalization, creating high-fidelity virtual replicas of physical assets that can be updated in real time (Rahman & Hossain, 2020). Digital twins can be created with data streams from IoT sensors.

Digital Twins and Cybersecurity

Cybersecurity Integration

Digitalization leads to increasing vulnerabilities. Cyber-physical attacks are a growing risk for the more interconnected cyber-physical systems. Contemporary designs should incorporate AI-enhanced systems for anomaly detection in order to safeguard model systems:

$$A(t) = |y(t) + \hat{y}\,(t)| > (\delta) \qquad (13)$$

Digital Twins

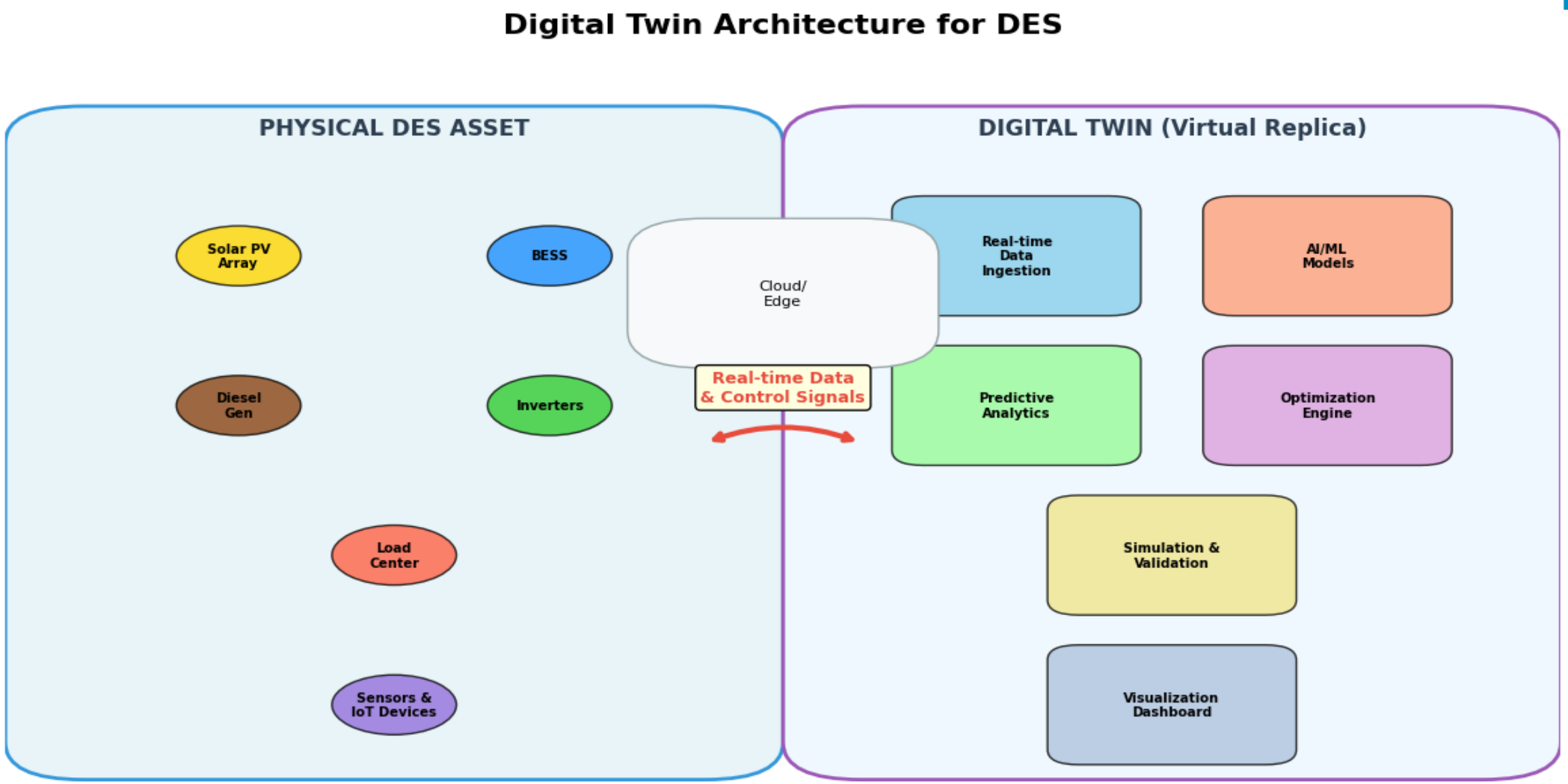


Figure 4: Digital twin architecture for DES (conceptual overview).

Methodological Novelty: Holistic Integrated Modelling (HIM)

Unified HIM Optimization Formulation

A compact representation of HIM is a single planning-and-operation problem that minimizes life-cycle cost while co-optimizing technical stability, risk, and socio-regulatory feasibility:

$$\min_{x,\, y_\omega} E_w\left[C_{inv}(x) + C_{op}(y_\omega + \omega)\right] + \beta.\mathcal{R}(x, y_\omega, \omega) + \gamma.S(x, y_\omega, \omega) \quad (15)$$

Here, x denotes planning decisions (DER capacities, topology, protection/controls), y_ω denotes operational decisions (dispatch, storage scheduling, demand response), ω denotes uncertainty (renewable/resource variability, load growth, fuel and FX prices), $C_{inv}(x)$ denotes Capital investment costs, $C_{op}(y_\omega + \omega)$ denotes Operational costs, $R(x, y_\omega, \omega)$ denotes Risk measure (e.g., financial, operational risk), $S(x, y_\omega, \omega)$ Socio-regulatory penalty/feasibility term and β and γ weight risk and socio-regulatory penalties/constraints consistent with the planning context.

Actuarial Risk Modelling: Chain Ladder Method

The Chain ladder is one of the most effective and widely used actuarial science tools, used to estimate by making use of historical developmental data; this tools have proven useful in insurance, finance etc.

$$f_j = \frac{\sum_i C_{i,j+1}}{\sum_i C_{i,j}} \tag{14}$$

Future cumulative value can be estimated as;

$$\hat{C}_{i,\,j+1} = C_{i,j} \cdot f_j \tag{15}$$

Where i denotes origin year (or project initiation year), j denotes development period, $C_{i,j}$ represents cumulative cost (or claims) observed.

TYPICAL EXAMPLE OF DISTRIBUTION ENERGY SYSTEM

- NIGERIA IMMIGRATION SERVICE HEADQUARTER SOLAR FARM (ABUJA)

  1.2 MWh ESS + 0.544 MWp ON/OFF GRID

  For powering up their data center

- UNIVERSITY OF ABUJA SOLAR FARM (ABUJA)

  7 MWH ESS + 3.5 MWp ON/OFF GRID

  For Powering up some part of the University

- LAFARGE/ Olorunsogo Power Plant (Ewekoro, Ogun State)

  14 MWh ESS + 18 MWp (Peak generation)

  This deployment basically for Cement factory

RESEARCH GAP AND PROPOSED HIM APPLICATION

Table 2: Fragmentation of DES modelling and HIM research mandate

Dimension	Current Modelling Gaps	HIM Research Mandate
Technical	• Focus on LCOE over stability • Inadequate cyber-resilience integration	• Integrated Stability & Optimization • Cyber-physical resilience models
Economic	• Static risk assumptions in LCOE • Ignoring non-energy benefits (NEBs) • One-size-fits-all tariff design	• Risk-Adjusted Viability Models • Dynamic risk assessment frameworks • Hybrid tariff optimization under uncertainty
Socio Regulatory	• Neglecting institutional friction in deployment • Limited community acceptance models • Skills gap unaccounted for in operations	• Socio-Technical Resilience Models • Regulatory sandbox integration • Local capacity building metrics

FRAGMENTATION OF DES MODELLING

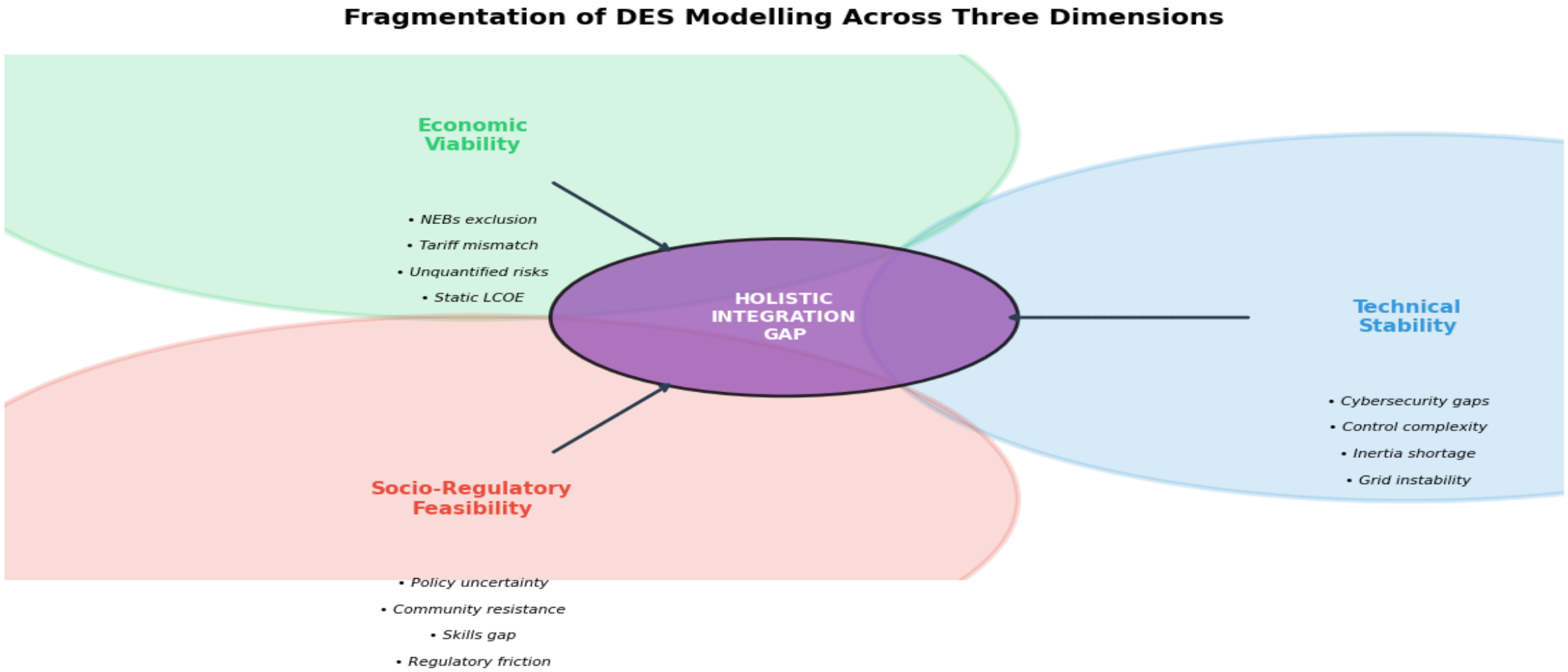


Figure 5: Proposed Holistic Integrated Modelling (HIM) framework integrating

CONCLUSION AND FUTURE RESEARCH

This review systematically articulates the current state of DES modelling, addresses the critical fragmentation, and in response proposes Holistic Integrated Modelling (HIM) as an anticipatory framing of the research agenda.

Future research must operationalize the HIM constructs to:

- Co-optimize technical stability and economic performance.
- Integrate dynamic risk assessment and adaptive tariff structures.
- Embed socio-regulatory constraints into quantitative tools.
- Integrated HIM formulation and simulation-based validation using representative case studies.

SIGNIFICANTS OF THIS REVIEW

The significant of this review are:

- framing the progress of DES modelling concerning sub-national grid autonomy;
- consolidating literature into a stability-economics-socio regulatory comparative framework; and
- structuring and integrating the HIM research agenda to stimulate further empirical investigations.

LIMITATIONS OF THE REVIEW

In the socio-regulatory context, the absence and unevenness of quantitative datasets limits the strict application of meta-analysis.

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