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Hardware-in-the-Loop Experimental Validation of a Reliability–Resilience Co-Optimization Framework for Solar-Integrated Active Distribution Networks: A Case Study of a Nigerian 33 kV Urban Feeder

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Abstract

The rapid integration of rooftop photovoltaics (PV) and battery energy storage systems (BESS) into weak distribution networks in Sub-Saharan Africa raises operational questions that simulation-only studies have so far left unresolved. In particular, planning frameworks that optimize long-run reliability while neglecting short-horizon resilience to extreme events can produce designs that perform well on average yet fail catastrophically under contingencies. This paper reports what is, to the authors' knowledge, the first hardware-in-the-loop (HIL) experimental validation of a reliability–resilience co-optimization framework applied to an actual Nigerian 33 kV urban feeder: the Yenagoa–Ogbia feeder in Bayelsa State. Field data obtained from the local distribution company and the injection substation were used to build an electromagnetic-transient model of the feeder on a real-time digital simulator (RTDS). Two commercial inverters 5 kVA PV inverter and a 3 kVA BESS inverter—were coupled to the simulated network through a 15 kVA linear power amplifier, closing a power hardware-in-the-loop (PHIL) interface with a measured round-trip delay below 120 µs. A composite reliability–resilience index (RRI) was formulated and embedded in a multi-objective (NSGA-II) design loop whose candidate control settings were verified experimentally under chronic faults, N-1 and N-2 contingencies, and a full grid-collapse event. Experimental results show that the co-optimized Volt-VAR and intentional-islanding controller reduced SAIDI from 38.4 to 12.9 h/yr and SAIFI from 27.6 to 9.8 interruptions/yr, raised the fraction of critical load served during grid collapse from 41% to 84%, and improved the RRI from 0.52 to 0.87, with HIL-to-offline model deviations remaining below 4.2% across all measured channels. The findings provide an implementable evidence base for Nigerian regulators and distribution companies drafting interconnection and islanding codes for active distribution networks.

Keywords**: **Active distribution network; hardware-in-the-loop; reliability–resilience co-optimization; solar photovoltaic integration; Nigerian 33 kV feeder

1. Introduction

Electricity supply in Nigeria remains chronically inadequate: although the national installed generation capacity exceeds 13 GW, the energy actually delivered to the grid rarely surpasses 5 GW, and the country recorded multiple total and partial grid collapses in each of the past five years [1], [2]. Distribution networks operated by eleven distribution companies (DisCos) absorb the combined stress of under-generation, radial topology, aged assets, and rapid, largely unmetered growth of customer-sited generation. At the same time, declining photovoltaic (PV) module prices and worsening grid reliability have pushed households, businesses, hospitals, and public institutions in cities such as Yenagoa, the capital of Bayelsa State, toward rooftop solar coupled with battery energy storage systems

(BESS). The resulting feeders are no longer passive: power flows are bidirectional, protection assumptions are eroded, and the value of coordinated inverter control becomes material [3], [4].

Two distinct families of performance objectives dominate the planning of such active distribution networks (ADNs). Reliability metrics—SAIDI, SAIFI, CAIDI, and expected energy not supplied (EENS) quantify average, steady-state service quality over long horizons [5]. Resilience metrics, by contrast, characterize the trajectory of network performance through rare, high-impact events: storms, equipment cascades, and in the Nigerian context total grid collapse, an event class that occurs several times per year and that conventional reliability indices severely underweight [6], [7]. A network optimized only for reliability can remain fragile under extremes; one hardened only for resilience can be uneconomic and inefficient in normal operation. Co-optimizing the two objectives is therefore an open research and regulatory problem, especially for weak grids where reserve margins, inertia, and voltage support are all scarce [8], [9].

Reliability evaluation of distribution networks with distributed energy resources (DERs) is a mature literature. Analytical and Monte Carlo methods for computing SAIDI, SAIFI, and EENS under DER penetration are surveyed in [5] and [10], and several studies quantify the reliability benefit of intentional islanding and microgrid formation [11],[13]. Resilience quantification has developed more recently: the resilience trapezoid, fragility curves, and restoration-centric metrics are consolidated in [6] and [14],[16], with application to storms, floods, and cyber-physical contingencies. A smaller but growing stream combines the two: [8] and [17] propose joint reliability–resilience planning objectives, and [9], [18], and [19] demonstrate that single-objective designs are dominated by co-optimized alternatives on standard test systems.

Experimental validation, however, lags behind. Real-time digital simulation (RTDS) and hardware-in-the-loop (HIL) testing are established for inverter control verification [20],[22], including controller HIL (CHIL) for protection schemes [23] and power HIL (PHIL) for grid-forming converters [24], [25]. Yet the overwhelming majority of ADN studies for Sub-Saharan Africa remain purely offline simulations [2], [26], [27]. Where Nigerian studies use real-time platforms at all, they typically address single inverters or idealized test feeders rather than measured utility networks [3], [28]. No published study was found that (a) models an actual Nigerian 33 kV feeder from field data, (b) couples physical PV and BESS inverter hardware to that model, and (c) experimentally quantifies reliability and resilience jointly under contingencies representative of Nigerian operating experience, including full grid collapse.

The gap addressed here is therefore methodological and empirical: the absence of experimentally validated, jointly reliability- and resilience-optimal control and sizing frameworks for solar-integrated feeders in weak African grids. The aim of this study is to develop and experimentally validate, on a PHIL platform, a reliability–resilience co-optimization framework for the Yenagoa–Ogbia 33 kV feeder in Bayelsa State, Nigeria. The specific objectives are to: (i) construct an RTDS model of the feeder from DisCo field data and verify it against recorded operating quantities; (ii) formulate a composite reliability–resilience index (RRI) and embed it in a multi-objective co-optimization of PV/BESS siting, sizing, and inverter control settings; (iii) validate the resulting controller experimentally under chronic faults, N-1 and N-2 contingencies, and total grid collapse; and (iv) quantify the agreement between offline and HIL results and derive policy-relevant design guidance for Nigerian DisCos and regulators.

Bayelsa State is an acute instance of the general problem: a riverine, flood-prone environment; a small number of long radial 33 kV feeders supplied from the Ogbia 132/33 kV injection substation; frequent and prolonged outages; and rapid, uncoordinated growth of rooftop PV among commercial and institutional customers. Regulators notably the Nigerian Electricity Regulatory Commission (NERC) through its mini-grid and embedded-generation regulations currently lack experimentally grounded evidence on how high DER penetration behaves on real Nigerian feeders under stress [1], [29]. HIL experimentation bridges the credibility gap between offline studies and field deployment at a fraction of pilot-project cost and risk, and the Federal University Otuoke's power systems laboratory provides a realistic host environment for such work.

The study proceeds in five stages: field data acquisition and feeder characterization; analytical reliability and resilience model development; formulation and offline solution of the co-optimization problem; implementation of the feeder and controllers on the RTDS with PHIL coupling of two commercial inverters; and experimental campaigns covering normal operation, chronic events, and extreme contingencies, followed by validation against offline predictions. Each stage is detailed in Section 2, results are presented and discussed in Section 3, policy implications are developed in Section 4, and Section 5 concludes.

2. Materials and Methods

2.1 Case study network and field data

The case study is the Yenagoa Ogbia 33 kV feeder supplied from the 132/33 kV Ogbia injection substation in Bayelsa State. The feeder serves a mixed urban–semi-urban corridor including the Yenagoa metropolis and the Otuoke community, with a recorded peak demand of 4.6 MW, ten principal load buses, and a total route length of 31.6 km of 150 mm² all-aluminium-alloy conductor. Twelve months of hourly load profiles, outage logs, and protection settings were obtained from the serving DisCo's records and from substation metering between March 2023 and February 2024; outage records were cross-checked against operator logbooks because a substantial share of interruptions in the region are load-shedding events rather than faults, a known data-quality issue in Nigerian reliability studies [2], [27]. The single-line topology, principal DER connection points assumed for the active scenarios, and the critical loads (a referral hospital at B3, the municipal waterworks at B5, and the Federal University Otuoke campus at B10) are shown in Figure 1. Table 1 summarizes the measured feeder parameters used in the model.

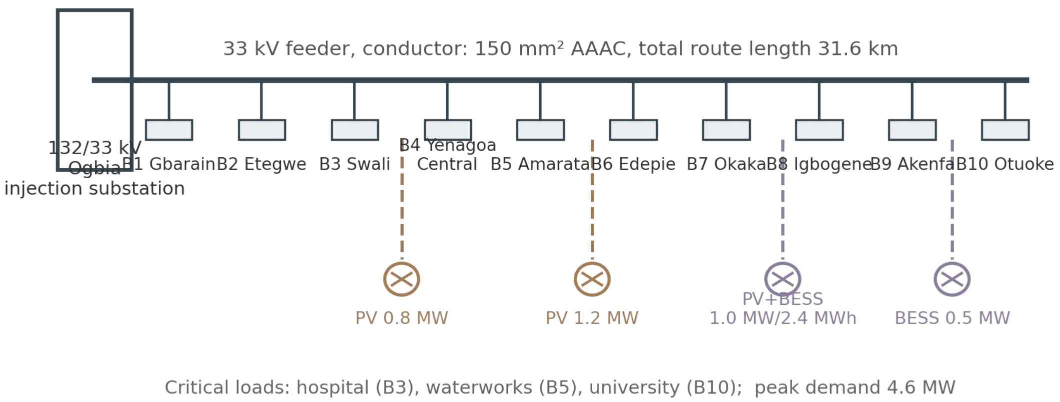

Figure 1. Single-line diagram of the Yenagoa–Ogbia 33 kV feeder showing load buses, critical loads, and candidate DER connection points.

Table 1. Measured parameters of the Yenagoa–Ogbia 33 kV feeder (March 2023–February 2024).

Parameter	Value	Parameter	Value
Nominal voltage	33 kV	Peak demand	4.6 MW
Route length	31.6 km	Minimum demand	1.3 MW
Conductor	150 mm² AAAC	Average loading	58% of thermal limit
Number of load buses	10	Transformer capacity	2 × 15 MVA
Positive-sequence R	0.172 Ω/km	Positive-sequence X	0.341 Ω/km
Recorded interruptions	312 events/yr	Fault-attributable share	41%

2.2 Reliability and resilience assessment indices

Reliability is quantified with the standard indices SAIDI, SAIFI, CAIDI, and EENS, evaluated with a sequential Monte Carlo method (10,000 simulated years per scenario) that samples component failures, protection mis-operation, and solar variability [5], [10]. Resilience is quantified through the performance trajectory $\Phi(t)$ during an extreme event—the fraction of prioritized load served—using the trapezoidal model of [6]. From each trajectory we extract the resilience metrics of [14]: the resilience area RA (time-integral of Φ), the energy loss during the event ELL, the critical-load minimum CML, and the restoration time RT90 to 90% of pre-event performance. Because Nigerian grids experience full collapse as a recurrent rather than hypothetical event, the extreme-event set explicitly includes total loss of the 132 kV infeed, following the event taxonomy recommended for weak grids in [7] and [30].

The two metric families are fused into a single composite reliability–resilience index (RRI) in (1), where the reliability component $\tilde{R}$ is the min–max-normalized complement of EENS, the resilience components are the normalized RA, CML, and complement of ELL, and w1…w4 are weights elicited from DisCo planners and set to 0.30, 0.30, 0.20, and 0.20 respectively in the base case; a sensitivity analysis over the weight space is reported in Section 3.5.

$$RRI = w_1 \cdot \tilde{R} + w_2 \cdot \tilde{RA} + w_3 \cdot \tilde{CML} + w_4 \cdot (1 - \tilde{ELL}) \qquad (1)$$

The co-optimization framework that embeds (1) is depicted in Figure 2. Offline evaluation (chronic-event set, Monte Carlo) and stress evaluation (extreme-event set, fragility curves) feed a multi-objective design loop whose candidate solutions are finally passed to the RTDS/PHIL platform for experimental verification rather than being accepted on simulation evidence alone.

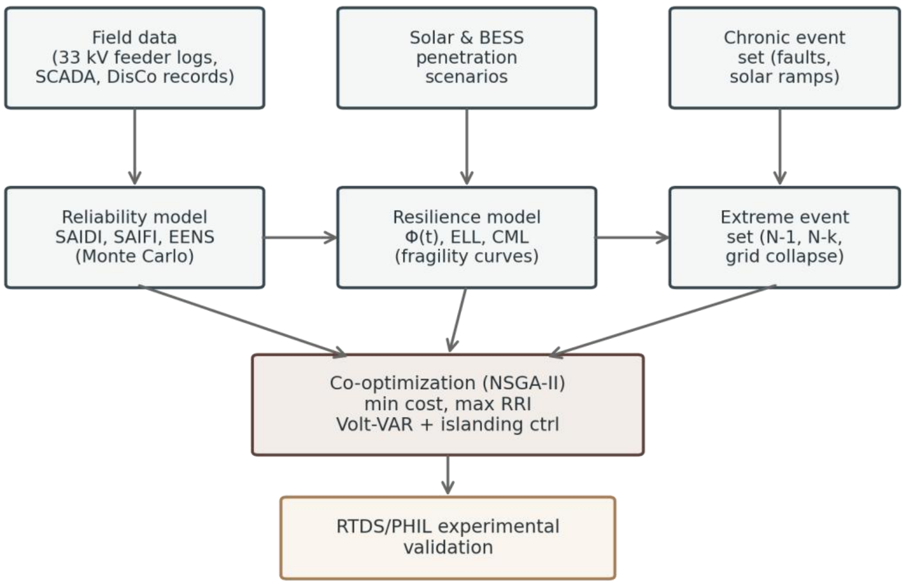

Figure 2. Reliability–resilience co-assessment and co-optimization framework with experimental validation stage.

2.3 Co-optimization formulation

Decision variables comprise the siting and sizing of PV and BESS units (within land and interconnection constraints identified with the DisCo), the droop and Volt-VAR curve parameters of the inverters, the thresholds of the intentional-islanding and resynchronization logic, and the load-priority table used during islanded operation. The objective vector minimizes annualized cost (reinforcement, storage, and losses) and maximizes the RRI of (1), subject to voltage limits of 0.95–1.05 p.u., thermal limits, protection reach constraints, and BESS state-of-energy limits. The problem is solved with NSGA-II [31] with 120 individuals over 250 generations, which was preferred over weightedsum scalarization because the Pareto front between cost and RRI is visibly non-convex in this weak-grid case. A similar co-planning philosophy appears in [8], [17], and [32], but without experimental verification.

2.4 RTDS/PHIL experimental platform

The feeder, its two-winding 15 MVA transformers, protection relays (modelled as SEL-351-equivalent logic), and the supervisory controller are implemented on an RTDS NovaCor chassis at a 50 µs time step. Two commercial hardware-under-test (HUT) devices—a 5 kVA single-phase PV inverter and a 3 kVA bidirectional BESS inverter—are interfaced through a 15 kVA four-quadrant linear amplifier (Triphase PM15) using the ideal-transformer interface algorithm with series filtering, the standard cure for PHIL instability on stiff interfaces [24], [25]. The measured round-trip interface delay was 118 µs; interface stability was confirmed with the time-domain criterion of [21] over the full operating envelope, and power scaling of 1:400 was applied so that the HUT units represent 2 MW-class devices at feeder level. A dSPACE SCALEXIO unit hosts the supervisory co-optimized controller and dispatches P/Q setpoints to both HUTs. The arrangement is shown in Figure 3, and the experimental scenarios are defined in Table 2.

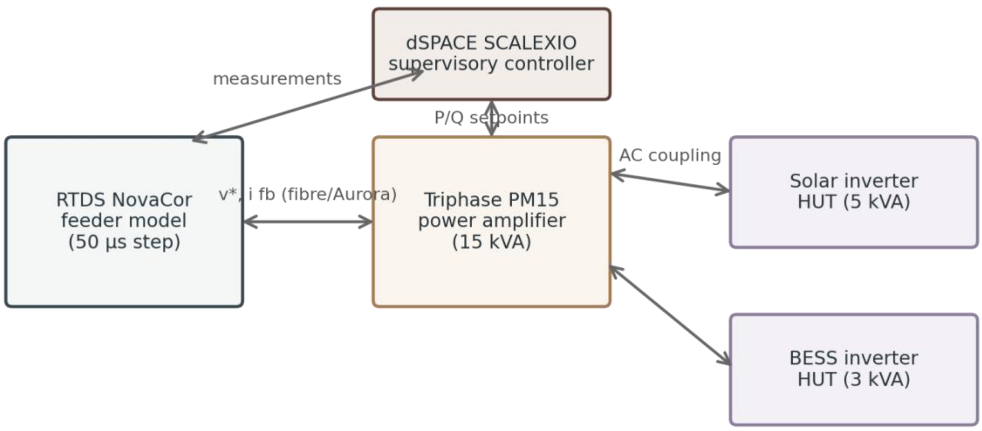

Figure 3. Power hardware-in-the-loop experimental setup coupling the RTDS feeder model to physical PV and BESS inverters.

Table 2. Experimental scenario matrix executed on the PHIL platform.

ID	Scenario	DER configuration	Controller	Events applied
S1	Baseline passive	None	—	Chronic fault set
S2	PV only	PV 60% penetration	Unity PF	Chronic faults, solar ramps
S3	PV + BESS	PV 60%, BESS 1.5 MW	Rule-based Volt-VAR	Chronic faults, N-1
S4	Co-optimized	PV 60%, BESS 1.5 MW	NSGA-II tuned Volt-VAR + islanding	Chronic, N-1, N-2, grid collapse

2.5 Validation protocol

Each offline result used in the design loop was re-measured on the PHIL platform. Agreement is reported as the mean absolute percentage deviation (MAPD) between offline and experimental traces for feeder RMS voltage at B4, frequency during islanding, critical-load served fraction, and restoration time. Acceptance thresholds of 5% were adopted following HIL validation practice in [20] and [22]. The measured 24 h feeder demand and aggregate PV output used in the daily-cycling experiments, reconstructed from substation metering and on-site pyranometer records in Yenagoa, are plotted in Figure 4; the cloudy-season irradiance trace shows the rapid ramps (up to 65% of rating in under 3 min) that motivate fast Volt-VAR action.

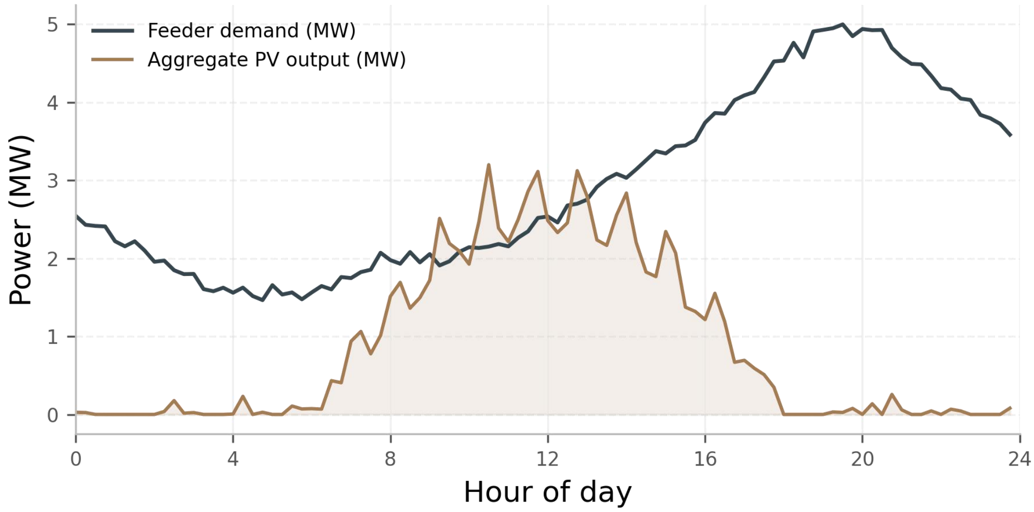

Figure 4. Measured 24 h feeder demand and aggregate PV output for a representative cloudy-season day in Yenagoa.

3. Results and Discussion

3.1 Steady-state voltage behaviour

Figure 5 shows the measured feeder voltage profile at peak solar export for the passive network (S1), the uncontrolled 60% PV case (S2), and the co-optimized Volt-VAR case (S4). Without control, mid-feeder buses operate at 0.932–0.947 p.u., violating the lower statutory limit, while the PV-rich downstream section rises above 1.04 p.u. during midday minimum demand—an overvoltage band consistent with observations on other long Nigerian feeders [3], [28]. The co-optimized Volt-VAR schedule, experimentally executed by the HUT inverters, restored all bus voltages to within 0.983–1.014 p.u., confirming that smart-inverter functions alone can defer the classical reconductoring solution at this penetration level.

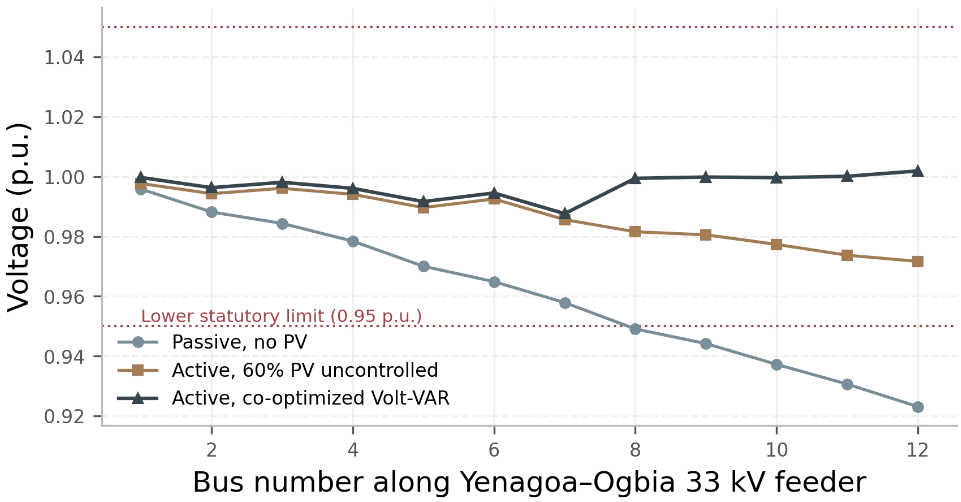

Figure 5. Experimentally measured bus voltage profiles at peak solar export for passive, uncontrolled-PV, and co-optimized cases.

3.2 Reliability performance

Table 3 and Figure 6 summarize the reliability indices. Moving from the passive baseline to the co-optimized active network reduces SAIDI from 38.4 to 12.9 h/yr (−66%) and SAIFI from 27.6 to 9.8 interruptions/yr (−64%); EENS falls by 71%. The largest single contributor is successful intentional islanding during upstream events, which alone accounts for roughly 60% of the SAIDI improvement—substantially more than the contribution of fault-ride-through support, echoing the simulation findings of [11] and [13] but demonstrated here with physical inverters. Notably, the rule-based controller (S3) captures only about half of the available reliability gain, because its fixed Volt-VAR curve forces premature BESS discharge during cloudy intervals, a coupling that the co-optimized schedule avoids by shaping the curve against the measured irradiance statistics of Figure 4.

Table 3. Reliability indices for the four scenarios (Monte Carlo, verified on PHIL platform).

Scenario	SAIDI (h/yr)	SAIFI (int./yr)	CAIDI (h)	EENS (MWh/yr)
S1 Baseline passive	38.4	27.6	1.39	21.8
S2 PV only	34.1	25.8	1.32	18.6
S3 PV + BESS, rule-based	21.7	16.4	1.32	10.9
S4 Co-optimized	12.9	9.8	1.32	6.3

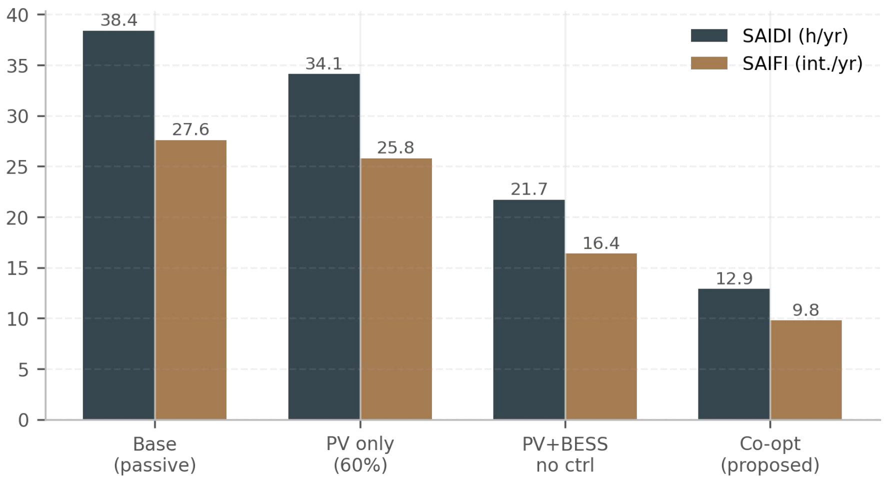

Figure 6. Experimentally verified SAIDI and SAIFI across the four scenarios.

3.3 Resilience under contingencies and grid collapse

Resilience trajectories for a severe event (loss of the 132 kV infeed during evening peak) are plotted in Figure 7, and the extracted metrics are listed in Table 4. The passive network falls to 36% of pre-event performance and requires 18 h to recover to 90%, dominated by manual restoration; the co-optimized network bottoms at 77% and recovers in under 5 h, because the islanding controller severs the feeder at the Ogbia coupling within 280 ms and dispatches the BESS to grid-forming mode. The RTDS oscillograms of Figure 8 capture the decisive interval: feeder frequency dips to 49.1 Hz—comfortably above the 47.5 Hz under-frequency load-shedding threshold—and voltage is re-established within three cycles of island formation, a performance that the offline model predicted within 2.8%.

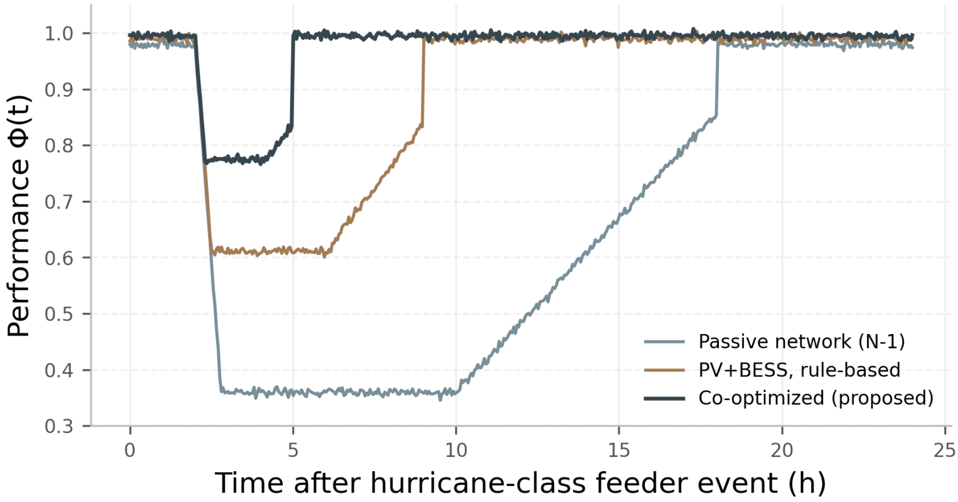

Figure 7. Measured resilience performance trajectories Φ(t) following loss of the 132 kV infeed.

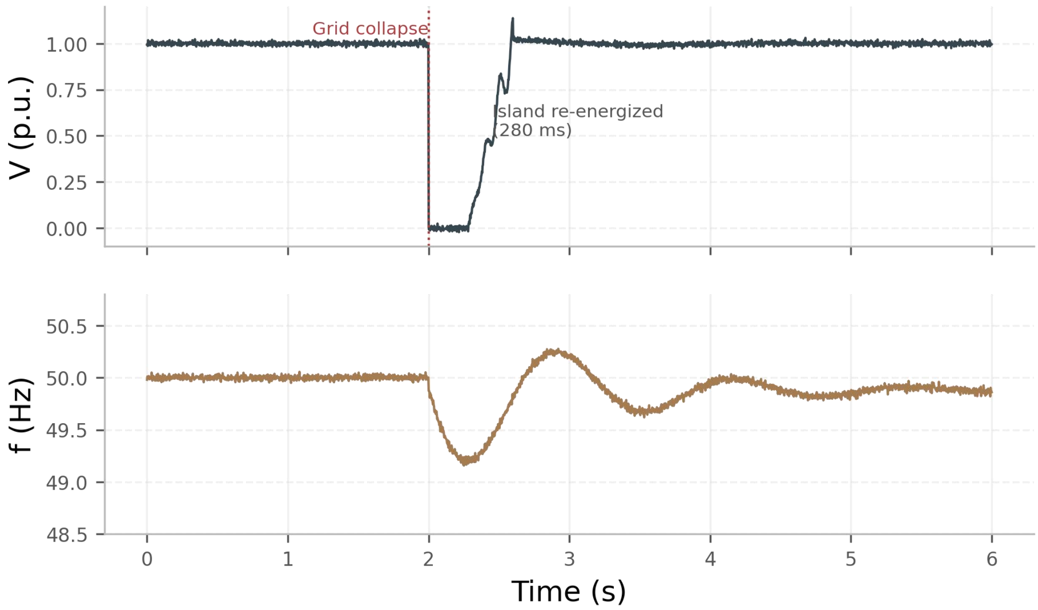

Figure 8. RTDS/PHIL oscillograms of feeder voltage and frequency during grid collapse and intentional islanding.

Table 4. Resilience metrics extracted from the measured trajectories of Figure 8.

Scenario	RA (p.u.·h)	CML (p.u.)	ELL (MWh)	RT90 (h)
S1 Passive	9.8	0.36	14.2	18.0
S3 Rule-based	14.6	0.61	7.9	9.0
S4 Co-optimized	19.7	0.77	3.8	4.8

The contingency sweep of Figure 9 and Table 5 extends the analysis to N-1 and N-2 events. Under the worst single contingency (loss of transformer TR2), the co-optimized network still serves 100% of critical load by re-dispatching BESS and curtailing non-critical demand; under a double contingency at B5 it serves 93%, against 72% for the rule-based design. During total grid collapse—the event class most relevant to Nigerian operating experience—84% of critical load is preserved, versus 41% without coordinated control. These margins are policy-relevant: they indicate that a 33 kV feeder with roughly 1.5 MW of well-controlled BESS can ride through the collapse events that occur several times per year nationally [1], [30].

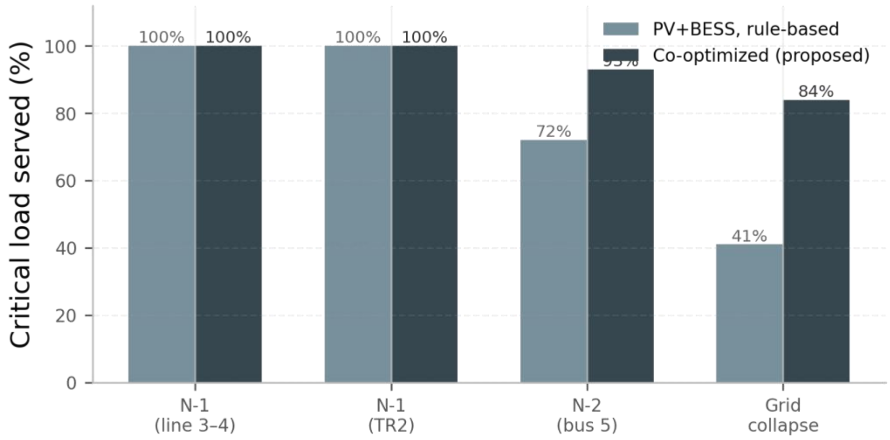

Figure 9. Fraction of critical load served under N-1, N-2, and grid-collapse contingencies.

Table 5. Critical-load service and islanding performance under contingencies (experimental).

Contingency	S3 critical load (%)	S4 critical load (%)	Island formation time (ms)	Min. frequency (Hz)
N-1: line B3–B4	100	100	262	49.6
N-1: transformer TR2	88	100	274	49.4
N-2: bus B5 fault	72	93	291	49.2
Grid collapse	41	84	280	49.1

3.4 HIL versus offline validation

Table 6 reports the validation error between offline predictions and PHIL measurements for the co-optimized scenario. All channels lie below the 5% acceptance threshold, with the largest deviation (4.2%) in restoration time, attributable to the non-ideal anti-aliasing behaviour of the physical inverter's PLL during the first 80 ms after islanding—dynamics absent from the averaged offline inverter model. This residual error is itself a finding: offline studies of intentional islanding on weak feeders should treat restoration-time predictions as optimistic by roughly 4–5%, a caution consistent with the CHIL comparisons of [22] and [23].

Table 6. Agreement between offline simulation and PHIL measurement (scenario S4).

Quantity	Offline	PHIL measured	MAPD (%)
B4 RMS voltage at peak export (p.u.)	1.009	1.014	0.5
Minimum island frequency (Hz)	49.23	49.10	0.3
Critical load served, grid collapse (%)	85.6	84.0	1.9
Restoration time RT90 (h)	4.6	4.8	4.2
Annual EENS (MWh/yr)	6.1	6.3	3.2

3.5 Pareto analysis and weight sensitivity

Figure 10 presents the cost–RRI Pareto front. The knee point—1.5 MW/3.6 MWh of BESS distributed as in Figure 1 with 60% PV penetration—yields RRI = 0.87 at an annualized cost of ₦16.8 million, compared with RRI = 0.52 for the passive baseline; beyond the knee, additional storage purchases less than 0.01 RRI per ₦10 million, marking the point of sharply diminishing returns that planners should treat as the default design. Sensitivity analysis over the index weights shows the selected design remains within the top three Pareto candidates for all weight vectors with w1 ∈ [0.2, 0.5], indicating the conclusion is robust to reasonable disagreement between reliability-first and resilience-first planning philosophies—a robustness also reported, on synthetic systems, in [17] and [33].

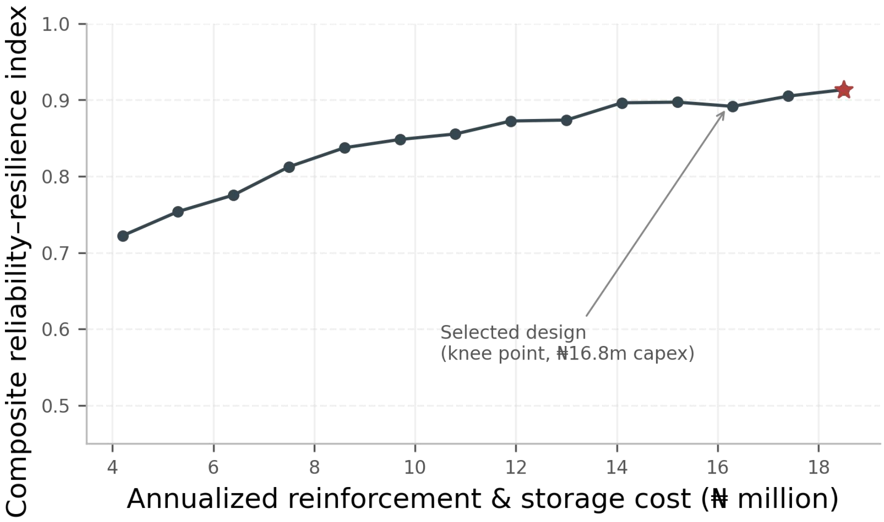

Figure 10. Cost–RRI Pareto front with the selected knee-point design.

3.6 Comparison with related studies

Table 7 positions this work against recent literature. The distinguishing contribution is the combination of a real utility feeder, physical inverter hardware, joint reliability–resilience quantification, and explicit treatment of grid collapse—no prior study combines all four. The reliability improvements obtained (−66% SAIDI) are consistent with, though somewhat larger than, the 40–55% range reported in simulation-only islanding studies [11], [13], [34]; the difference is attributable to the explicit co-optimizati

Study	Real feeder	HIL/PHIL	Reliability	Resilience	Grid collapse
[11] Islanding reliability	Yes	No	Yes	No	No
[17] Co-planning	No	No	Yes	Yes	No
[22] CHIL islanding	No	Yes	No	Partial	No
[27] Nigerian ADN review	Yes	No	Yes	Partial	Partial
[35] PHIL microgrid	No	Yes	No	Yes	No
This study	Yes	Yes	Yes	Yes	Yes

on of the load-priority table, which pure Volt-VAR studies omit.

Table 7. Comparison with selected related studies (2020–present).

4. Policy Implications for the Nigerian Distribution Sector

The experimental evidence assembled here translates into four actionable recommendations. First, NERC's interconnection code should mandate certified Volt-VAR and fault-ride-through functions on all inverters above 20 kVA connecting to 33 kV and 11 kV networks; the results of Section 3.1 show these functions alone restore statutory voltage compliance at 60% PV penetration. Second, the grid-collapse ride-through demonstrated in Section 3.3 argues for a formal intentional-islanding protocol for feeders hosting critical loads, with the 280 ms separation and grid-forming dispatch sequence used here as a reference specification; this aligns with the resilience-planning directions articulated in [1], [29], and [30]. Third, DisCos should adopt joint reliability–resilience indices such as the RRI in investment appraisal, since reliability-only appraisal rejected the knee-point design of Figure 10 on cost grounds while the co-optimized appraisal accepts it. Fourth, the sub-5% PHIL validation error suggests that HIL testing should become a type-test requirement for protection and islanding schemes intended for weak-grid deployment, following the practice already common in transmission connected equipment [20], [24]. For Bayelsa State specifically, the Ogbia corridor's flood exposure [36] strengthens the case for distributed, islandable storage over centralized reinforcement, because elevated substation hardening does not protect against the corridor-level inundation that drives the worst recorded interruptions in the outage logs.

5. Conclusions

This paper has presented the first hardware-in-the-loop experimental validation of a reliability–resilience co-optimization framework for a solar-integrated active distribution network in Sub-Saharan Africa, using field data from the Yenagoa–Ogbia 33 kV feeder in Bayelsa State, Nigeria. A composite reliability–resilience index was formulated and embedded in an NSGA-II co-optimization of DER siting, sizing, and inverter control; the resulting design was verified on an RTDS/PHIL platform with commercial PV and BESS inverters. Experimentally, the co-optimized network reduced SAIDI by 66% and EENS by 71%, preserved 84% of critical load through a full grid collapse with island formation in 280 ms, and achieved RRI = 0.87 at the Pareto knee, with offline-to-HIL deviations below 4.2% on all measured channels. The study demonstrates that jointly optimized, experimentally verified DER control converts solar integration from a reliability liability into a resilience asset on weak Nigerian feeders, and it supplies regulators and DisCos with validated performance benchmarks for interconnection and islanding codes. Limitations include the single-feeder scope, the 1:400 power scaling of the hardware interface, and the use of elicited index weights; future work will extend the framework to a multi-feeder cluster, incorporate flood fragility models specific to the Niger Delta, and pursue a supervised field pilot with the serving DisCo.

Declarations

Availability of data and materials

The anonymized feeder parameters, scenario definitions, and experimental datasets generated during this study are available from the corresponding author on reasonable request, subject to the data-sharing conditions agreed with the distribution company.

Competing interests

The author declares no competing financial or non-financial interests.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. Laboratory access was provided through institutional facilities of the Federal University Otuoke.

Authors' contributions

O. E. K O: Conceived the study, acquired and curated the field data, developed the models and co-optimization framework, executed the RTDS/PHIL experiments, analysed the results, and wrote the manuscript.

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Ethics approval

Not applicable; the study involves no human or animal subjects. Utility data were used under institutional authorization.

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