



Availability Modelling and Cost-Optimal Preventive Maintenance Scheduling of a Residential Off-Grid Photovoltaic System



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ABSTRACT: Off-grid photovoltaic systems supply a growing share of Nigerian households, yet maintenance follows generic manufacturer schedules rather than quantitative local cost and reliability assessment. This paper develops a framework coupling component-level failure-time modelling, series reliability block diagram aggregation and imperfect preventive maintenance optimisation under a Kijima Type I virtual-age model, applied to a 4.2 kVA system in a University of Ilorin staff-quarters apartment. Reliability parameters are literature-derived priors because the installation operated only about 1.5 months without failure; all intervals and savings are therefore model-derived estimates, not field-validated recommendations. Unavailability is valued at ₦500 per kWh against an annual demand of 3,504 kWh from the household load inventory, covering component outages only, not loss of load from low irradiance or battery depletion. Under the default schedule, technical availability is 0.99630 at an annual ownership cost of ₦220,687. The optimised policy gives 0.99661 and ₦145,617, saving 34.0%. This saving mainly removes planned replacement: the replacement limit is not reached within design life, and almost all battery renewals become failure-driven, raising exposure to unplanned expenditure. Estimated major service intervals are 16.9 months for the battery bank and 31.9 months for the inverter, with 90% ranges of 11.3-23.9 and 21.2-47.4 months under joint parameter uncertainty. The battery governs availability under adopted component lifetimes, reversing only if its characteristic life exceeds 15.0 years. This framework offers a practical basis for tailoring preventive maintenance and reducing ownership costs in Nigerian off-grid PV households, though field validation is required before adoption.

KEYWORDS: Off-Grid Photovoltaic System, Operational Availability, Imperfect Preventive Maintenance, Virtual Age, Value of Lost Load.

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I. INTRODUCTION

Access to reliable electricity remains one of the most enduring constraints on the development in sub-Saharan Africa, where roughly 600 million people lacked access in 2023 (Ehimen et al., 2023; Yeboah et al., 2026). Nigeria accounts for about 85 million of these, the largest un-electrified population in the world (Adeyemi-Kayode et al., 2022; Emmanuel, 2025). Access statistics understate the problem, because a grid connection frequently delivers fewer than twelve hours of supply a day, with wide variation across geographical zones, distribution companies and customer bands (Migisha et al., 2023; Pelz et al., 2023). Households and firms respond by self-generating, so the marginal value they place on continuous supply is set not by the regulated tariff but by the cost of the alternatives they already buy. That distinction governs any economic treatment of downtime and underpins the cost model developed here. Off-grid and hybrid photovoltaic (PV) systems are the principal technical response. Falling module costs and incremental gains in lead-acid and lithium storage have brought residential solar within reach of a growing share of Nigerian households (Babajide & Brito, 2021; Tansu et al., 2022), while global horizontal irradiance of 4.5 to 6.5 kWh/m²/day yields capacity factors well above those of most European installations (Chanchangi et al., 2023). More than a million standalone systems have been sold under Rural Electrification Agency programmes (Singh & Singh, 2025), so deployment is no longer the limiting factor in household electrification. What happens after commissioning has received far less attention, and that is the subject of this work.

A typical Nigerian installation comprises five subsystems with distinct failure modes, repair routes and maintenance

requirements: the PV generator, direct current wiring and protection, the battery bank, the inverter, and the AC distribution panel. Reviews of PV operation and maintenance consistently find structured agreements and procedures routine on large grid-connected plant but rare on small distributed installations (Abdulla et al., 2024; Gonzalo et al., 2020). Owners of residential systems follow either generic manufacturer schedules or routines built from personal experience, neither informed by the cost and reliability trade-offs of their own operating environment. The result is a systematic over-maintenance of some subsystems and under-maintenance of others. Residential off-grid systems also differ structurally from the grid-connected systems that dominate the reliability literature. Cost pressure at this scale eliminates redundancy: a single photovoltaic string feeds a single charge controller, a single battery bank and a single inverter stage, so failure of any element on the energy path disables the whole system. There is no grid to fall back on and, in this installation, no auxiliary generator. Storage is absent from grid-tied systems altogether, yet here it is both the largest single capital item and, as this paper shows, the binding reliability constraint. Conclusions drawn from utility-scale studies therefore transfer to this setting only with care.

Reliability engineering offers established tools for this class of problem. The age-replacement policy of Barlow & Hunter (1960) establishes that for components with an increasing hazard rate there exists an interval minimising long-run cost per unit time. That policy assumes each preventive action restores the component to an as-good-as-new state, which describes residential PV servicing poorly. Imperfect maintenance models, in which an intervention removes only

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part of the accumulated age, were introduced for exactly this situation (Kijima, 1989; Nakagawa, 1988; Pham & Wang, 1996), and this paper adopts one. Reliability block diagrams, fault tree analysis, continuous-time Markov chains and Monte Carlo simulation provide complementary routes to system availability and have all been applied to PV systems (Maihulla & Yusuf, 2022; Nallainathan et al., 2020; Sonawane et al., 2023; Torres Navarro et al., 2025). Three gaps remain. First, component reliability parameters for the local environment are largely unquantified, because manufacturers derive lifetimes from temperate-climate test conditions unlike Nigerian ambient temperature, dust loading and electrical stress; field studies report annual module degradation of 1.23% to 1.65% in Ghana (Aboagye et al., 2021, 2022) and 0.99% to 1.15% in East Africa (Ngure et al., 2022), against a global median of approximately 0.5% and mean of 0.8% (Jordan & Kurtz, 2013). Second, system availability is rarely aggregated through a defensible logical structure. Third, maintenance intervals are rarely optimised against an explicit economic objective incorporating the value of unserved energy.

This paper addresses those gaps using a 4.2 kVA off-grid system installed at a residential apartment in the University of Ilorin staff quarters. Four contributions follow. A computational framework is developed combining Weibull and exponential failure-time modelling, series reliability block diagram aggregation and imperfect preventive maintenance optimisation under a virtual-age model, with a discrete-event Monte Carlo check. A complete parameter set is assembled and declared explicitly as literature-derived priors, together with a formal statement of the observational evidence needed to displace them. Under those priors the optimised schedule reduces expected annual ownership cost by 34.0% (₦75,071) at zero capital outlay, a saving arising mainly from removing planned replacement, and a joint uncertainty analysis reports the range of that estimate. Finally, for the adopted component lifetimes the battery bank rather than the inverter limits availability, and the characteristic life at which this ordering reverses is identified. Sections II to IX cover related work, the case study system and component reliability model, availability and imperfect maintenance, the optimisation problem, parameterisation and the operational record, results and discussion, limitations, and conclusions.

II. RELATED WORK

Five bodies of work bear on this paper. Component-level reliability studies establish failure mechanisms for components of the PV subsystems and their lifetime distributions and provide parameters fed into any system-level model. System-level methods provide the machinery by which component behaviour is aggregated into an availability figure. The maintenance literature supplies the policy structure and the parameters of the optimisation. Parameters obtained from the temperate area can be rightfully applied to the tropics and Africa only when field tests have been conducted there. Finally, consider off-grid deployment in sub-Saharan Africa to set the framework of the operating context and of the economic interests. The review draws mainly on papers indexed in the IEEE, Elsevier, Springer and Wiley databases, with emphasis on work published since 2020; earlier works are included where they are standard references for theory or parameter values.

A. Component-Level Reliability of Photovoltaic Subsystems

The PV modules are the most visible element of an installation but are not often the constraints. Aboagye et al. (2021) evaluated sixteen long-commissioned installations in Ghana and found that after an operating period of more than five years, the mean degradation rates for monocrystalline, polycrystalline and amorphous silicon were 1.23%, 1.35% and 1.65%, respectively, concluding that approximately half of the installed modules will reach end-of-life in less than 15 years (Aboagye et al., 2021). The results of a study in three climatic zones in Ghana showed crystalline silicon as consistently outperforming amorphous silicon, whereas the degradation under test in the interior savannah region was the worst for all technologies studied, and operating temperature and dust deposition were revealed as the most dominant accelerating stresses (Aboagye et al., 2022). Khan et al. (2024) synthesised two decades of reported failure mechanisms and found the prevalence of each to depend strongly on site climate. Failure modes and effects analysis performed by Pimpalkar et al. (2023) came to a similar conclusion.

B. Inverter Reliability

It is a commonly recognized fact that the most vulnerable part of the system in grid-connected systems is the inverter (Golnas, 2012). Alavi et al. (2024) modelled a 4 kW grid-connected inverter under three climate-driven degradation scenarios using physics-based capacitor and IGBT lifetime models with Monte Carlo sampling, showing that neglecting module degradation causes inverter life to be overestimated, particularly in hot climates. Kull et al. combined laboratory short circuit test with destructive field testing of a large plant and showed that catastrophic failures were caused by slowness of the isolation relay response and insufficient semiconductor protection margin and inadequate internal protection coordination (Kull et al., 2025). Remy et al. (2025) applied stochastic Markov modelling to a five-level quasi Z-source inverter. Electrolytic capacitor wear in the DC link is the mechanism underlying most of this behaviour (Wang & Blaabjerg, 2014). Every one of these studies concerns grid-connected hardware, where no storage subsystem competes for the role of bottleneck.

C. Storage and Balance-of-System Reliability

In off-grid systems, competition regarding storage and balance-of-system reliability exists and storage generally wins it. The dominant degradation mechanisms of flooded tubular lead-acid cells, positive grid corrosion, sulphation at partial state of charge, water loss and shedding of active mass, are long established (Ruetschi, 2004; Sauer & Wenzl, 2008), and their rates are strongly temperature-dependent. In several Sub-Saharan African Countries, battery replacement was determined as the most significant operating expenses of solar home systems and the major constraint encountered when operating them (Aitio & Howey, 2021). Aitio & Howey (2021) used field data from a fleet of off-grid installations to predict battery end of life, demonstrating both the feasibility and the data requirements of empirical lifetime estimation at scale, a point returned to in Section VI-E. Balance-of-system components, cabling, surge protection, fuses and breakers, are conventionally assigned constant failure rates drawn from IEEE

Std 493-2007, since their failures arise from external events rather than progressive ageing.

D. System-Level Reliability and Availability Methods

There are four general approaches to system-level assessment. The reliability block diagrams assume binary (also called dichotomous) failure mode of components and independence and represent the logical dependence of system failure on component failure in series, parallel and k-out-of-n structures, and are computationally inexpensive. Fault tree analysis is deductive in nature, starting from an undesired top event and moving down through logic gates towards the causes of the top event; Sonawane et al. (2023) applied it to the direct current side of a large-scale plant and Nageh et al. (2021) used a comparable approach across alternative inverter configurations. Markov state-space methods represent the system as discrete states connected by failure and repair transitions; Maihulla & Yusuf (2021, 2022) applied reliability, availability, maintainability and dependability analysis to grid-connected systems. The state space grows exponentially with component count, and a constant-rate formulation cannot represent either Weibull wear-out or deterministically scheduled maintenance, which is why the present work does not adopt it. In contrast, Monte Carlo simulation does not have such restrictions since it samples lifetimes directly (Nallainathan et al., 2020).

A systematic review by Torres Navarro et al. (2025) confirmed that reliability, availability and maintainability are directly linked to photovoltaic system performance, and observed that whole-system analysis rather than component analysis in isolation remains a recurring and only partially met need. The present work responds to that observation and additionally addresses a scale, residential and off-grid, that the reviewed literature does not cover. Reliability block diagram aggregation is used as the primary route and discrete-event Monte Carlo simulation as an independent check, set out in Section VII-G. Standard treatments of the underlying theory are given by Billinton and Allan (1985), Birolini (2010) and Modarres et al. (2016).

E. Maintenance Strategy and Imperfect Maintenance

Maintenance regimes are classified as corrective, preventive and condition-based. Gonzalo et al. (2020) surveyed maintenance management for photovoltaic systems and found preventive maintenance comparatively under-studied relative to fault detection. Osmani et al. (2020) and Abubakar et al. (2021) also carried out a review of the strategies across the value-chain and reached similar conclusions. Marangis et al. (2025) compared corrective, preventive, predictive and extraordinary maintenance with the instrumentation provided by Internet-of-Things (IoT) and machine-learning (ML) techniques and found that there was a large difference between installations at the utility-scale plant and small distributed installations. Ahmed et al. (2025) reviewed predictive maintenance and identified the indirect measurability of component state as a persistent obstacle.

A common limitation is the availability of instrumentation; condition-based methods assume that there is sensing infrastructure, this is not available in low-income settings. Formal optimisation of preventive intervals goes back to Barlow & Hunter (1960), whose age-replacement policy assumes that each preventive action renews the component completely. That

assumption is untenable for the servicing performed on residential photovoltaic hardware, where equalisation charging, electrolyte correction and capacitor replacement improve condition without restoring it to new. Imperfect maintenance models address this directly. Kijima (1989) introduced the virtual-age formulation in which an intervention reduces effective age by a factor rather than to zero, and Nakagawa (1988) developed sequential imperfect policies with replacement after a fixed number of interventions; Pham & Wang (1996) survey the field. Ali et al. (2025) applied an incomplete, non-periodic model to photovoltaic plants through service-age regression, obtaining cost reductions of 21.4% and 6.22% with availability gains of 0.24% and 0.03%, confirming that the economic return to optimisation substantially exceeds the availability return.

F. Tropical Operating Environments and Off-Grid Deployment in Nigeria

Photovoltaic degradation is sensitive to ambient temperature, humidity, dust deposition and ultraviolet exposure. In East Africa, under current condition in the savanna in the warm climate region, Ngure et al. (2022) used current-voltage tracing, infrared thermography technology and normal NREL methods to determine that the degradation rates of six years were 0.99% per year for monocrystalline modules and 1.15% per year for polycrystalline modules. Mohamad Radzi et al. (2025) conducted a 36-month evaluation in a tropical environment under IEC 61724 and obtained efficiency losses ranging from 5.31% to 9.94%. Taken with the Ghanaian evidence (Aboagye et al., 2021, 2022), and against the analytical baselines of Jordan & Kurtz (2013) and Vázquez & Rey-Stolle (2008), these correspond to rates between 1.2 and 3.3 times the global median. Parameters transferred without adjustment will therefore overstate component life in Nigerian conditions.

Discussions of residential systems in Nigeria are still primarily a design/performance concern rather than reliability concern. Adesina et al. (2023) designed, built and tested an off-grid system for a Nigerian household of similar size to the one studied here, and concluded that battery sizing and protection govern reliability. Babalola et al. (2022) conducted a study on the socio-economic effects of a hybrid mini-grid in southwestern Nigeria, and they noted the positive impacts on enterprise creation and employment, which assumes a steady and reliable operation. Karthik & Ponnambalam (2025) proposed a fault tolerant approach for a home based system. Mukisa et al. (2022) strongly pointed out that it is not nominal capacity but operational reliability for residential systems. All of these don't measure system availability nor come up with an economically optimal maintenance schedule.

G. Synthesis and Research Gap

The reviewed literature is summarised in Table 1, which states the focus and method of each work, its principal findings and the outstanding limitation. Three observations follow. The analytical machinery used for PV availability evaluation is well developed but are being used almost entirely for grid connected and utility-scale PV installations. Tropical field studies show that the reliability parameters used in temperate zones cannot be taken as a direct reference for use in Nigeria, and there is no study that contains a modified parameter set for an off-grid residential configuration. There is a large amount

of experience with formal preventive maintenance optimisation in wind and large-scale photovoltaic plants and not at all for residential off-grid plants in sub-Saharan Africa. What is absent is not any individual method but their

combination, parameterised for this operating context, formulated under a maintenance model that matches the servicing actually performed, and checked against an independent simulation.

Table 1 Summary of reviewed literature on photovoltaic reliability, maintenance optimisation and off-grid deployment.

Reference	Focus and method	Key findings	Limitation or gap
Aboagye et al. (2021, 2022)	Field degradation across three Ghanaian climatic zones	Degradation 1.23-1.65 %/yr; temperature and dust dominant	Degradation only; no availability or maintenance model
Ngure et al. (2022)	Six-year outdoor exposure, I-V tracing, IR thermography	0.99 %/yr mono-Si and 1.15%/yr poly-Si degradation	Reliability and maintenance not modelled
Mohamad Radzi et al. (2025)	36-month IEC 61724 assessment, tropical climate	Efficiency falls 5.31-9.94 %; tropical ageing confirmed	Grid-connected performance only; no cost analysis
Khan et al. (2024)	Review of two decades of module failure mechanisms	Failure modes strongly dependent on site climate	Qualitative; no quantitative availability model
Golnas (2012); Alavi et al. (2024)	Operator field records; Monte Carlo with capacitor and IGBT models	Inverter dominates unavailability; hot climates shorten life	Grid-tied only; no maintenance-interval optimisation
Kull et al. (2025)	Laboratory and field diagnosis of inverter failures	Failures traced to slow relay response, weak protection	Diagnostic case study; no system availability model
Maihulla & Yusuf (2021, 2022)	RAMD analysis, Markovian and Chapman-Kolmogorov methods	Subsystem expressions derived for all four RAMD metrics	Constant-rate; cannot represent wear-out or scheduled PM
Torres Navarro et al. (2025)	Systematic review of RAM analysis for grid-connected PV	RAM directly linked to performance; identifies critical items	Whole-system and off-grid analysis unaddressed
Sonawane et al. (2023); Nageh et al. (2021)	Fault tree analysis of large-scale plants with cost evaluation	Critical DC-side components and failure probability identified	Utility scale; no maintenance scheduling
Nallainathan et al. (2020)	Monte Carlo simulation of renewable-rich microgrids	Resource and equipment stochastics modelled jointly	Microgrid scale; no optimal schedule derived
Barlow & Hunter (1960)	Renewal-theoretic age-replacement policy	Optimal PM interval minimising long-run cost rate	Assumes as-good-as-new renewal at every intervention
Kijima (1989); Nakagawa (1988)	Virtual-age and sequential imperfect maintenance policies	Intervention reduces effective age by a factor, not to zero	General theory; not applied to off-grid PV systems
Gonzalo et al. (2020); Osmani et al. (2020)	Surveys of PV maintenance management and strategy	Preventive maintenance understudied vs fault detection	Qualitative; no quantitative scheduling framework
Marangis et al. (2025); Ahmed et al. (2025)	Reviews of preventive, predictive, condition-based maintenance	Formal O&M contracts rare in small distributed plants	Predictive methods need sensors absent at residential scale
Abdulla et al. (2024)	Bibliometric review of PV O&M, 2010-2023	Optimised O&M recovers about 5 % of lost energy	Review; no case-specific optimisation model
Ali et al. (2025)	Incomplete, non-periodic maintenance optimisation	Cost savings 21.4 % and 6.22 %; availability gains 0.24 %, 0.03 %	Large-scale plants in a different parameter regime
Mukisa et al. (2022); Aitio & Howey (2021)	SHS economics; fleet-data battery life prediction	Battery replacement is the largest operating cost	No maintenance scheduling or availability model
Adesina et al. (2023); Babalola et al. (2022)	Nigerian household system design; mini-grid impact	Battery sizing governs reliability; enterprise gains	Design and impact only; no availability or PM analysis

III. SYSTEM DESCRIPTION AND COMPONENT RELIABILITY MODEL

The model developed here is of intermediate fidelity. A full physics-of-failure treatment resolving encapsulant chemistry, electrolyte transport and semiconductor junction temperature would be defensible for any single component but would require parameters no residential installation can supply. A purely algebraic treatment assigning each subsystem a constant availability could not represent wear-out, which is the mechanism that makes preventive maintenance worth scheduling at all. The formulation adopted describes each component by a failure-time distribution matched to its dominant physical failure mode, and aggregates those descriptions through the logical structure of the installation. This section fixes the physical system, develops the distributions, and states the aggregation rule together with the assumptions it rests on.

A. Case Study Installation

The installation analysed is a 4.2 kVA off-grid photovoltaic system serving a residential apartment in the staff quarters of the University of Ilorin, Nigeria, at approximately

8.48° N and 4.54° E. The site lies within the Guinea savannah climatic zone, and records of the Nigerian Meteorological Agency give a mean global horizontal irradiance of about 5.5 kWh/m² per day, peaking between February and April. The apartment has no utility connection and no auxiliary generator, so the photovoltaic-battery system is its sole source of supply. Ambient temperatures frequently exceed 30 °C, which bears directly on the storage parameters adopted in Section VI. The installation provides a case study representative of the class of residential systems considered in this analysis.

Five subsystems lie along a single energy path, shown in Figure 1. The photovoltaic generator comprises four 580 W monocrystalline modules connected as one series string, giving a nameplate capacity of 2,320 Wp. Direct current power is carried over twelve metres of 6 mm² copper cable terminating in a combiner box containing a fuse and a surge protection device. Storage is provided by two 12 V, 220 Ah flooded tubular lead-acid batteries in series, forming a 24 V bus with a nominal capacity of 5.28 kWh. A 4.2 kVA hybrid inverter integrates maximum power point tracking, battery management and the DC-AC conversion stage. Alternating current is distributed through a main miniature circuit breaker, sub-circuit breakers and a residual current device.

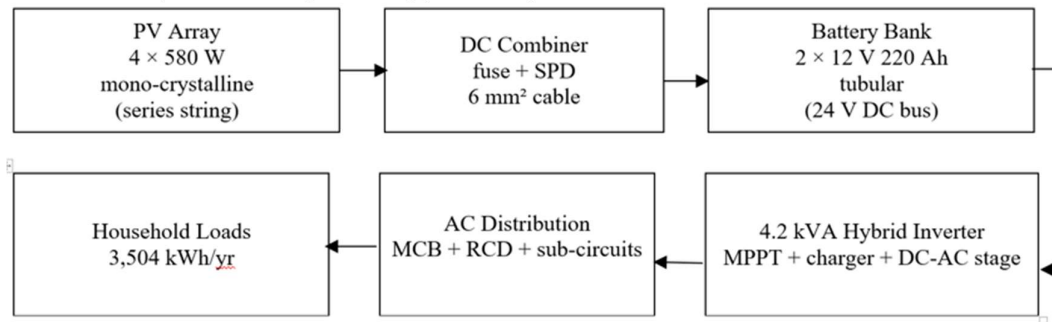


Figure 1 Single-line arrangement of the case study system.

Household energy demand is 9.6 kWh per day, sustained by a mean load of 0.8 kW across an average of twelve operating hours, giving an annual demand of 3,504 kWh. This figure is an estimate derived from the household load inventory, not a metered value. A 2,320 Wp array at the site irradiance of 5.5 kWh/m² per day and a performance ratio of 0.75 yields approximately 9.6 kWh per day, which shows only that the array was sized to this estimate and does not independently confirm it. An uncertainty of ±20% is therefore attached to the annual demand, reflecting typical variation in

appliance ratings and hours of use. Because the demand scales the value of lost load term in (28) and the denominators of both levelised cost metrics, its effect is reported in Sections VII-E and VII-I, and it is sampled in the joint uncertainty analysis of Section VII-J. Capital expenditure taken from the project invoice totals ₦1,644,000, comprising ₦1,526,000 in materials, ₦8,000 in logistics and ₦110,000 in workmanship. The invoice is used later not only as a capital figure but as the source of the replacement costs in Section VI-C. Table 2 gives the breakdown.

Table 2 Capital cost breakdown of the case study system, taken from the project invoice.

Item	Quantity	Unit cost (₦)	Total cost (₦)
4.2 kVA hybrid inverter	1	340,000	340,000
220 Ah tubular battery	2	260,000	520,000
580 W solar module	4	130,000	520,000
Solar DC cable (6 mm ²)	12 m	4,000	48,000
Roof mounting rail	1 length	13,000	13,000
Battery rack	1	15,000	15,000

Item	Quantity	Unit cost (₦)	Total cost (₦)
Protection breaker box	1	25,000	25,000
Electrical cables	-	-	30,000
Other accessories	-	-	15,000
Total material cost			1,526,000
Logistics	-	-	8,000
Workmanship	-	-	110,000
Overall total			1,644,000

B. Failure-Time Description

Let T denote the time to first failure of a component placed in service at $t = 0$. Its probabilistic description rests on the density $f(t)$, the cumulative distribution $F(t)$, the reliability function $R(t)$ and the hazard rate $z(t)$. The reliability function is the probability of survival beyond t and is the complement of the cumulative distribution, as given in (1).

$$R(t) = P(T > t) = 1 - F(t) \quad (1)$$

The hazard rate is the conditional density of failure at t given survival to t , and is the quantity that encodes the physical failure mechanism. It is defined in (2). A constant hazard corresponds to random failures, an increasing hazard to wear-out, and a decreasing hazard to early-life defects.

$$z(t) = \frac{f(t)}{R(t)} \quad (2)$$

The reliability function may be recovered from the hazard rate through the exponential of its negative integral, as in (3). The integral appearing there is the cumulative hazard, written $\Lambda(t)$ in (4), and it is the quantity through which the maintenance model of Section IV operates.

$$R(t) = \exp\left(-\int_0^t z(\tau) d\tau\right) \quad (3)$$

$$\Lambda(t) = \int_0^t z(\tau) d\tau = -\ln R(t) \quad (4)$$

C. Exponential and Weibull Models

Components whose failures arise from external events rather than progressive ageing exhibit a constant hazard rate, $z(t) = \lambda$. Substituting into (3) yields the exponential reliability function of (5), whose mean time between failures is the reciprocal of the failure rate as given in (6). The exponential distribution is memoryless, so a surviving component has the same residual life distribution as a new one. In this work it is applied to the direct current cabling

and surge protection assembly and to the alternating current distribution panel, whose failures are dominated by lightning surges, mechanical damage and connector corrosion.

$$R(t) = e^{-\lambda t} \quad (5)$$

$$\text{MTBF} = \int_0^\infty R(t) dt = \frac{1}{\lambda} \quad (6)$$

Components subject to wear-out require an increasing hazard rate, and the two-parameter Weibull distribution provides the standard description. Its reliability function is given in (7), the corresponding cumulative hazard in (8), the hazard rate in (9), and the mean life in (10), where Γ denotes the gamma function. The characteristic life η is the time at which approximately 63.2% of a population has failed, and is not the same quantity as the mean life; the distinction matters in Section VI-D.

$$R(t) = \exp\left(-\left(\frac{t}{\eta}\right)^\beta\right) \quad (7)$$

$$\Lambda(t) = \left(\frac{t}{\eta}\right)^\beta \quad (8)$$

$$z(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1} \quad (9)$$

$$\mu = \eta \Gamma\left(1 + \frac{1}{\beta}\right) \quad (10)$$

The Weibull distribution with $\beta > 1$ is applied to the photovoltaic modules, the tubular batteries and the hybrid inverter, each of which degrades progressively through a documented physical pathway. Table 3 summarises the two families and the quantities derived from them. The assignment of a distribution family to a component is a modelling commitment rather than an estimation result, and it is defended in Section VI-A against the failure mechanisms reported in Section II. Where that defence is weakest, notably for the hybrid inverter, the sensitivity analysis of Section VII-E quantifies the consequence.

Table 3 Failure-time distributions used in this work.

Distribution	Reliability $R(t)$	Hazard rate $z(t)$	Mean life	Applied to
Exponential	$e^{-\lambda t}$	λ (constant)	$\frac{1}{\lambda}$	DC cabling and SPD; AC distribution
Weibull ($\beta > 1$)	$\exp\left(-\left(\frac{t}{\eta}\right)^\beta\right)$	$\frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1}$	$\eta \Gamma\left(1 + \frac{1}{\beta}\right)$	PV modules; tubular battery; hybrid inverter

D. Reliability Block Diagram and Its Assumptions

System availability is obtained by aggregating component availabilities through the logical structure of the installation. In a series structure, failure of any element disables the system, and system availability is the product of component availabilities under an assumption of statistical independence, as expressed in (11), where k denotes the number of identical units in class i .

$$A_{\text{sys}} = \prod_{i=1}^m A_i^{k_i} \quad (11)$$

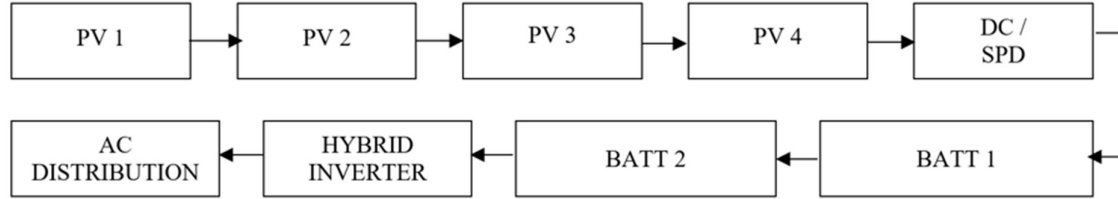


Figure 2 Reliability block diagram of the case study system.

Applying (11) to this structure gives the system availability expression of (12), in which module and battery availabilities enter raised to the number of series units in each class. Every term is bounded above by unity, so the product is strictly smaller than its smallest factor. This compounding is why a system built from components each individually above 0.998 available can nonetheless spend more than a day per year out of service. Equation (12) is applied to availabilities that contain corrective downtime only. Planned outages are treated separately. A quarterly battery visit, an array cleaning or an inverter service withdraws the whole class at once, so its duration is deterministic and simultaneous across the units of that class, and raising a per-unit availability that contains planned downtime to the power k_i would count the same outage k_i times. Planned downtime is therefore subtracted once at system level, as in 12, where A_i is the per-unit availability with respect to corrective outage defined in (22), U_{PM} is the planned-maintenance unavailability of all classes defined in (23) and U_{ro} is the routine-maintenance unavailability of (26). Visits to different classes are assumed not to coincide, which is conservative.

$$A_{\text{sys}} = (A_{\text{PV}}^c)^4 \cdot A_{\text{DC}}^c \cdot (A_{\text{B}}^c)^2 \cdot A_{\text{HYB}}^c \cdot A_{\text{AC}}^c \cdot (1 - U_{\text{PM}} - U_{\text{ro}}) \quad (12)$$

where A_{sys} is the system operational availability; A_{PV}^c , A_{DC}^c , A_{B}^c , A_{HYB}^c and A_{AC}^c are the per-unit availabilities with respect to corrective outage, defined in (22), of the photovoltaic module, the direct current cabling and surge protection assembly, the tubular battery, the hybrid inverter and the alternating current distribution panel respectively. Two assumptions embedded in (11) require explicit justification. The first is statistical independence. This is defensible for the dominant mechanisms, since encapsulant degradation, positive-grid corrosion and DC-link capacitor wear proceed through unrelated physical pathways and at unrelated rates. It is weaker for stresses acting on the whole installation at once. A lightning surge may damage the surge protection device, the inverter input

The case study installation is series throughout, with no redundancy at any point, and its reliability block diagram is shown in Figure 2. The four modules are series-connected within one string, so failure of any single module interrupts the string. The two batteries are series-connected to form the 24 V bus. A single combiner, a single inverter and a single distribution panel complete the path. This architecture is characteristic of low-cost residential systems and is what makes preventive maintenance economically consequential: there is no second path to carry load while a failed element is repaired.

stage and the distribution panel in a single event; sustained high ambient temperature accelerates battery and capacitor ageing simultaneously; and heavy dust deposition affects all four modules together. Common-cause dependence of this kind would reduce system availability below the value computed here, so the reported figures are optimistic in this respect. A beta-factor treatment of common cause would refine the estimate and is left to further work.

The second assumption is that failure of any single module disables the string. In practice a partially shaded, cracked or hot-spotted module may continue to pass current through its bypass diodes, producing derated rather than zero output. Treating such events as total failures is conservative, and combined with the series structure it places a lower bound on the availability of the generation subsystem. The assumption is least accurate for gradual power loss and most accurate for open-circuit failures such as junction-box or interconnect fracture, which do interrupt the string completely. The two assumptions therefore act in opposite directions, and no claim is made that they cancel.

IV. AVAILABILITY AND IMPERFECT MAINTENANCE MODELLING

Section III described how each component fails. This section describes how it is maintained and restored, and combines the two into the availability measure on which the optimisation acts. The central modelling decision is made here. Classical age replacement assumes that every preventive action returns the component to an as-good-as-new condition, so that the cost of that action is properly the cost of replacing it. That assumption does not describe the servicing performed on residential photovoltaic hardware, where equalisation charging, electrolyte correction, cell substitution and capacitor replacement improve condition without renewing the component. Applying age-replacement mathematics while costing the intervention as a service is internally inconsistent, and this section avoids that inconsistency by adopting a virtual-age formulation instead.

A. Availability Definition and Maintainability

Taking repair time to be exponentially distributed with mean MTTR, the maintainability function of (13) gives the probability that a repair, once begun, is completed within time t . For a component with exponential failures and repairs, the long-run availability follows from the balance between failure and repair rates and is given in (14).

$$M(t) = 1 - \exp(-t / \text{MTTR}) \quad (13)$$

$$A = \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}} \quad (14)$$

Three availability variants are distinguished in the reliability literature according to which sources of downtime enter the denominator. Inherent availability counts random failures and active repair only. Achieved availability adds planned preventive maintenance. Operational availability further adds administrative and logistical delay. Because the mean time to repair values adopted in Section VI-A are inflated above manufacturer service times to reflect parts-importation lead time and technician scarcity in Nigeria, the quantity computed throughout this paper is operational availability. It is written simply as A , and the term is used consistently in every table and figure that follows.

One further boundary of the model should be stated at the outset. The quantity A is a technical availability: it is the long-run fraction of time for which every component of the energy path is functional. It is not service availability. An off-grid system can fail to serve load while fully functional, through insufficient irradiance across consecutive overcast days, depletion of battery state of charge, demand exceeding instantaneous generation and storage capacity, or conversion losses. Technical availability is therefore an upper bound on service availability, and the loss-of-load probability of the installation is necessarily higher than $1 - A$. The value of lost load term introduced in Section V accordingly prices unserved energy caused by component outage only, and not the total loss-of-load cost of the system. Accordingly, wherever this paper refers to operational availability, it means the operational availability of the component chain in this technical sense.

B. Virtual Age and the Imperfect Maintenance Policy

The policy modelled is periodic imperfect preventive maintenance with replacement after a fixed number of services. A component is serviced at intervals T . Each service removes part but not all of the accumulated age, so that under the Kijima Type I formulation the virtual age entering the service interval indexed j is given by (15), where q is the improvement factor. Setting $q = 0$ recovers classical age replacement, in which each service renews the component completely, while $q = 1$ gives minimal repair, in which the service restores function without reducing age at all.

$$v_j = j q T, \quad j = 0, 1, \dots, N-1, \quad 0 \leq q \leq 1 \quad (15)$$

Because the component enters interval j at virtual age v_j and operates for real time T , the hazard accumulated during that interval is the increment of the cumulative hazard between v_j and $v_j + T$, as given in (16). Summing these increments gives the effective cumulative hazard at the end of interval j , stated in (17), and the corresponding survival probability follows in (18).

$$\Delta\Lambda_j = \Lambda(v_j + T) - \Lambda(v_j) \quad (16)$$

$$H_j = \sum_{l=0}^{j-1} \Delta\Lambda_l \quad (17)$$

$$S_j = \exp(-H_j) \quad (18)$$

The component is renewed either by failure, which occurs with probability $1 - S_n$ over the N intervals, or by scheduled replacement at the N -th service, which occurs with probability S_n . The expected uptime accumulated over one renewal cycle is obtained by integrating the survival function across each interval, as given in (19), and the expected number of services actually reached before renewal is given in (20).

$$E[U] = \sum_{j=0}^{N-1} \int_0^T \exp(-H_j - \Lambda(v_j + t) + \Lambda(v_j)) dt \quad (19)$$

$$E[n] = \sum_{j=1}^{N-1} S_j \quad (20)$$

where $E[U]$ is the expected uptime accumulated over one renewal cycle, $E[n]$ is the expected number of scheduled services reached before renewal, T is the service interval, N is the replacement limit, $v_j = jqT$ is the virtual age entering the j th interval, $\Lambda(\cdot)$ is the Weibull cumulative hazard, H_j is the cumulative hazard accrued up to the start of the j th interval, and $S_j = \exp(-H_j)$ is the probability of surviving to that point. Expected downtime per renewal cycle combines the service outages, the corrective repair should the component fail, and the outage associated with scheduled replacement, as given in (21). The scheduled replacement does not include the mean time to repair, since the replacement of the component has been planned and the component has been purchased, the time only for replacement itself is taken into account, whereas the mean time to repair includes time for diagnosis, unscheduled procurement and callout time. This choice works against the conclusions of this paper rather than in their favour: charging planned replacement at the mean time to repair instead would lower default availability from 0.99630 to 0.99428, an additional 17.7 hours; "only 0.6 hours of downtime per year, while lowering optimised availability by only 0.6 hours, because the optimised policy performs very few scheduled replacements. The assumption therefore favours the default policy and understates the advantage reported in Section VII-C. Operational availability of the component class then follows in (22) as the ratio of expected uptime to expected cycle length. The factor 8760 converts durations expressed in hours into years.

$$E[D] = \frac{\text{MPMT} \cdot E[n] + \text{MTTR}(1 - S_N) + \text{MPMT} \cdot S_N}{8760} \quad (21)$$

$$A_i^c = \frac{E[U]}{E[U] + \frac{\text{MTTR}(1 - S_N)}{8760}} \quad (22)$$

$$U_{PM} = \sum_i \frac{\text{MPMT}_i(E[n_i] + S_{N,i})}{8760(E[U_i] + E[D_i])} \quad (23)$$

where $E[D]$ is the expected downtime per renewal cycle, A_i^c is the operational availability of class i with respect to corrective outage, MPMT and MTTR are the mean preventive maintenance time and mean time to repair in hours, S_N is the probability of reaching the replacement limit without failing. Equation (22) includes planned outage and is used to define the renewal cycle length in (24). For system aggregation the

planned and corrective parts are separated. The per-unit availability with respect to corrective outage is given in (22), and the planned-maintenance unavailability, counted once per visit to each class, is given in (23), where $MPMT_i$ is the duration of one visit to the whole of class i and all units of a class are serviced together.

C. Cost Model

Three distinct cost events arise within a renewal cycle and must be distinguished, since conflating them is precisely the error that a service-priced age-replacement model commits. The cost of one scheduled service is C_s , the cost of replacing the component following failure is C_e and includes an unscheduled logistics premium, and the cost of planned replacement at the N -th service is C_r . Expected cost per renewal cycle is given in (24), and the long-run cost rate follows in (25).

$$E[C] = C_s E[n] + C_f(1 - S_N) + C_r S_N \quad (24)$$

$$c_i(T, N) = \frac{E[C]}{E[U] + E[D]} \quad (25)$$

where $E[C]$ is the expected cost per renewal cycle and $c_i(T, N)$ is the long-run cost rate per unit of class i at service interval T and replacement limit N . A category of maintenance activity remains outside this structure. Certain tasks are performed at a frequency fixed by physical necessity rather than chosen by the optimiser, and their omission would invalidate the characteristic lives adopted in Section VI. For the flooded tubular battery bank these are quarterly distilled-water top-up, terminal cleaning and equalisation. They are represented by the fixed annual cost and fixed annual downtime of (26), where n_{ro} is the number of routine visits per year. Because these terms do not depend on T or N they do not shift the location of the optimum, but they must appear in both the reported cost and the reported availability.

$$C_{ro} = n_{ro} c_{ro}, \quad U_{ro} = \frac{n_{ro} d_{ro}}{8760} \quad (26)$$

where C_{ro} is the cost of one routine visit and d_{ro} is its duration in hours, so that C_{ro} is the fixed annual cost of routine maintenance and U_{ro} the corresponding annual unavailability.

V. OPTIMISATION FORMULATION

The framework of Sections III and IV determines availability and cost rate once the maintenance decisions are fixed. This section makes those decisions the variables and states the economic objective. The objective is total annual cost of ownership, which for an off-grid household comprises what is spent on scheduled servicing, what is spent replacing components whether on failure or by plan, what is spent on routine tasks, and the economic loss incurred while the system is unavailable. The last term is the one most often omitted and it is the one that prevents the optimiser from extending every interval indefinitely.

A. Decision Variables

Each Weibull component class contributes two decisions, the service interval and the number of services before planned replacement, collected in (27). The direct current and alternating current assemblies have constant failure rates and derive no benefit from age-based intervention, so they are held at annual

inspection and excluded. The photovoltaic modules are a special case treated in Section VII-C: their improvement factor is close to unity because washing does not reverse encapsulant ageing, so their cleaning interval is fixed at twelve months on soiling and energy-yield grounds and only their replacement limit is optimised.

$$x = [(T_{PV}, N_{PV}), (T_B, N_B), (T_{HYB}, N_{HYB})] \quad (27)$$

where x is the decision vector; T_{PV} , T_B and T_{HYB} are the service intervals in years of the photovoltaic module, tubular battery and hybrid inverter classes respectively; and N_{PV} , N_B and N_{HYB} are the corresponding replacement limits, each being the number of scheduled services a component of that class undergoes before planned replacement.

B. Value of Lost Load

Because the system is off-grid with no generator backup, the cost of unavailability cannot be estimated from avoided tariff or avoided fuel. It is instead valued through the value of lost load, the amount a consumer would pay to avoid losing a unit of energy. A base case of ₦500/kWh is adopted, anchored on Nigerian willingness-to-pay evidence which places household willingness to pay in the region of ₦210 to ₦224 per kilowatt-hour and the cost of the reliability households already purchase through self-generation between ₦378 and ₦574 per kilowatt-hour (Oseni, 2017), with firm-level outage cost estimates for sub-Saharan Africa corroborating the order of magnitude (Oseni & Pollitt, 2015). The annual cost of unavailability follows in (28).

$$C_u = VOLL \cdot E_a(1 - A_{sys}) \quad (28)$$

Here E_a is the annual electrical energy actually demanded by the household, not the product of a nominal power rating and the full 8,760 hours of the year. The distinction matters because unavailability incurs economic loss only during hours in which energy would otherwise have been consumed. With the estimated annual demand of 3,504 kWh from Section III-A, equation (28) evaluates to ₦1,752,000 multiplied by system unavailability, so each 0.001 of unavailability costs approximately ₦1,752 per year. Consistent with Section IV-A, this prices only the unserved energy attributable to component outage, and not that arising from irradiance shortfall or state-of-charge depletion.

C. Objective Function and Constraints

The objective is the total annual cost of servicing, replacement, routine tasks and unavailability, summed over all component classes and given in (29). Each class contributes its cost rate multiplied by the number of units, and the unavailability penalty enters once at system level through the availability of (12). Constraints reflect physical and operational limits on the decisions, as stated in (30).

$$\min C(x) = \sum_i^m k_i c_i(T_i, N_i) + C_{ro} + VOLL \cdot E_a(1 - A_{sys}(x)) \quad (29)$$

$$0.25 \leq T_i \leq T_{i,m}, \quad 2 \leq N_i \leq 40, \quad N_i \in \mathbb{Z} \quad (30)$$

where $C(x)$ is the total annual cost under decision vector x , k_i is the number of units in class i , $c_i(T_i, N_i)$ is the per-unit annual cost rate of that class at service interval T_i and replacement limit N_i , C_{ro} is the fixed annual cost of routine battery

maintenance, and the final term is the unavailability cost of (28) evaluated at the system availability resulting from x , $T_{i,m}$ is the upper bound on the service interval of class i , set at its characteristic life, and the replacement limit N_i is restricted to the integers from 2 to 40. The problem is a mixed-integer non-linear program: the intervals are continuous while the replacement limits are integer. It is solved by separable decomposition: each component class is optimised on its own cost rate, and the resulting policy is then evaluated against the full objective. The decomposition is not exact, because the unavailability term couples the classes through system availability, but the coupling is weak: that term accounts for approximately 4% of total annual cost. The decomposition was verified against a joint search over all classes simultaneously, which returned a policy differing in cost by 0.03%, and the verification is reported in Section VII-C. Renewal integrals in (19) are evaluated by composite trapezoidal quadrature on sixty nodes per interval, and the interval search uses a tolerance of 10^{-8} years. The influence of each input parameter on optimised availability is quantified by the normalised sensitivity index of (31), evaluated by forward finite difference with a relative perturbation of 10% as in (32).

$$S_\theta = \frac{\partial A_{sys}}{\partial \theta} \cdot \frac{\theta}{A_{sys}} \quad (31)$$

$$S_\theta \approx \frac{A_{sys}(\theta + \Delta\theta) - A_{sys}(\theta)}{A_{sys}(\theta) \cdot \Delta\theta / \theta} \quad (32)$$

where S_θ is the dimensionless sensitivity of system availability A_{sys} to an input parameter θ , and gives the percentage change in A_{sys} produced by a 1% change in θ . where $\Delta\theta = 0.1\theta$ is the applied perturbation and $A_{sys}(\theta)$ and $A_{sys}(\theta + \Delta\theta)$ are the availabilities at the base and perturbed values, with the optimised policy held fixed.

VI. CASE STUDY PARAMETERISATION

A framework is only as credible as the numbers fed into it, and this section states where every number comes from. The position taken is deliberately conservative. The installation had

been in service for approximately one and a half months at the time of analysis with no recorded failure, which is far too short an exposure to estimate any failure rate. Rather than presenting literature values as though they were field estimates, this section declares them as priors, defends each against the physical failure mechanism it represents, sets out the temperature argument by which temperate-climate values are transferred to the site, and then quantifies exactly what observational evidence would be required to displace them.

A. Reliability Parameters

Table 4 lists the adopted parameters with their sources. The photovoltaic modules take $\beta = 1.5$ and $\eta = 25$ years, reflecting gradual encapsulant degradation, hot-spot formation and bypass-diode ageing (Jordan & Kurtz, 2013; Vázquez & Rey-Stolle, 2008). The tubular batteries take $\beta = 3.0$, characteristic of the wear-out phase in cycling tests, with $\eta = 6.5$ years (Ruetschi, 2004; Sauer & Wenzl, 2008). The hybrid inverter takes $\beta = 2.0$ and $\eta = 12$ years, governed by electrolytic capacitor wear in the DC link and switch-mode supply (Golnas, 2012; Wang & Blaabjerg, 2014). Mean times to repair are inflated above manufacturer service times to reflect Nigerian repair logistics, in particular parts-importation lead time and the limited availability of technicians certified on imported equipment. The constant failure rates of the DC cabling and surge protection assembly and of the AC distribution panel are taken from IEEE Std 493-2007, which compiles failure data for industrial and commercial installations. Their transfer to a residential installation rests on the similarity of the failure mechanisms: in both settings, low-voltage cables, terminations, fuses, breakers and surge devices fail mainly through external events such as surges, mechanical damage and connector corrosion rather than through wear-out. The transfer is not exact. Residential installations generally receive less skilled installation and less frequent inspection than the industrial sites in the source data, and may face more severe surge and corrosion exposure, so the adopted rates are more likely to be optimistic than pessimistic. The consequence is bounded in two ways: neither rate appears among the five most influential parameters in Table 13, and the joint uncertainty analysis of Section VII-J samples both rates from half to three times their adopted values.

Table 4 Component reliability parameters and their sources.

Component	Distribution	B	η (yr)	λ (yr ⁻¹)	MTTR (h)	MPMT per visit (h)	Source
PV module ($\times 4$)	Weibull	1.5	25	-	24	2	(Jordan & Kurtz, 2013; Vázquez & Rey-Stolle, 2008)
DC cabling / SPD	Exponential	-	-	0.030	8	1	(Society & Committee 493-2007)
Tubular battery ($\times 2$)	Weibull	3.0	6.5	-	48	3	(Ruetschi, 2004; Sauer & Wenzl, 2008)
Hybrid inverter	Weibull	2.0	12	-	72	4	(Golnas, 2012; Wang & Blaabjerg, 2014)
AC distribution	Exponential	-	-	0.020	8	1	(Society & Committee 493-2007)

B. Temperature Transfer of Reference Values

The adjustment from temperate-climate reference values to the site values of Table 4 rests on a temperature-acceleration argument, which is stated explicitly here because a claim of local parameterisation is otherwise unverifiable. For lead-acid storage the halving of service life for each 10 °C rise in mean operating temperature above 25 °C is a long-established empirical rule grounded in the Arrhenius dependence of grid corrosion (IEEE, 2006; Ruetschi, 2004), and an equivalent rule applies to the electrolytic capacitors that govern inverter life (Wang & Blaabjerg, 2014). The acceleration factor is given in (33).

$$AF = 2^{\frac{T_{\text{site}} - T_{\text{ref}}}{10}} \quad (33)$$

With a reference temperature of 25 °C and a mean battery-enclosure and inverter-cabinet temperature of 32 °C at the site, (33) gives $AF = 1.62$. The adopted characteristic lives of 6.5 years for the battery bank and 12 years for the inverter therefore correspond to reference lives of approximately 10.6 and 19.5 years respectively at 25 °C, both of which lie within the range quoted by manufacturers of this class of equipment.

No comparable acceleration model is applied to the photovoltaic modules, whose adopted characteristic life is taken directly from tropical field studies rather than transformed from a temperate baseline. The 32 °C figure is an estimate for the site enclosure and is identified in Section VIII as a parameter requiring direct measurement.

C. Maintenance Cost Parameters and the Improvement Factor

Three cost parameters are required per Weibull class, corresponding to the three events distinguished in (24). The scheduled service cost C_s covers technician time and consumables. The failure replacement cost C_e covers the component, unscheduled labour and a short-notice logistics premium. The planned replacement cost C_r covers the same component with scheduled labour and no premium. Replacement costs derive from the invoice of Table 2, with workmanship allocated in proportion to the labour required. Table 5 gives the resulting values together with the improvement factor adopted for each class

Table 5: Maintenance cost parameters and improvement factors.

Component	C_s , service (₦)	C_e , failure (₦)	C_r , planned (₦)	q	Basis for q
PV module (per unit)	1,500	155,000	148,000	0.90	Washing does not reverse encapsulant ageing
DC cabling / SPD	3,000	35,000	-	-	Constant hazard; no age reduction
Tubular battery (per unit)	4,500	280,000	270,000	0.40	Equalisation and cell substitution restore capacity
Hybrid inverter	8,000	380,000	360,000	0.30	DC-link capacitor replacement and re-pasting
AC distribution	3,000	35,000	-	-	Constant hazard; no age reduction

The improvement factor is the least well determined parameter in the model and is treated accordingly. It cannot be measured from the six-week operating record, so it is assigned from the physical character of each intervention and from its meaning under the Kijima Type I model. Under (15), each interval of length T adds only qT to the virtual age, so a service removes the fraction $1 - q$ of the age accrued since the previous service (Kijima, 1989). In practical terms, $q = 0.40$ means that a battery bank serviced every 16.9 months ages by about 6.8 months per interval, and after ten services carries the hazard of a bank about 5.6 years old rather than 14.1 years old.

For the flooded tubular battery, ageing combines reversible mechanisms, chiefly sulphation at partial state of charge and acid stratification, which equalisation charging and electrolyte correction largely recover, with irreversible mechanisms, chiefly positive grid corrosion and shedding of active mass, which no service reverses (Ruetschi, 2004; Sauer & Wenzl, 2008). The value $q = 0.40$ represents a major service that recovers the reversible share, taken here as about 60% of the ageing accrued between services under the partial-state-of-charge cycling typical of off-grid use, together with substitution of individually weak cells. For the hybrid inverter, $q = 0.30$

represents a service that replaces the DC-link and auxiliary-supply electrolytic capacitors, which are the dominant wear-out element in this class of converter (Wang & Blaabjerg, 2014), and renews the thermal interface material and cleans the cooling path, which lowers the operating temperature of the remaining parts; the unrecovered 30% represents ageing of semiconductors, solder joints and circuit boards that the service does not address. For the modules, $q = 0.90$ because washing removes soiling but does not reverse ultraviolet or thermal ageing of the encapsulant. Because these values remain engineering judgements rather than measurements, Section VII-D reports the sensitivity and regret of the optimised schedule across the full admissible range of q , and Section VII-J samples q jointly with the other uncertain inputs. Both analyses should be read as part of the result rather than as an appendix to it.

D. Treatment of the Operational Record

At the time of analysis the installation had operated for approximately one and a half months, 1,095 hours per unit, with no recorded failure of any component. This is too short an exposure to support failure-rate estimation, and it is reported

here only to document the observation period and to support the requirement calculation of Section VI-E. For a zero-failure observation the one-sided lower confidence bound on mean time between failures follows from the chi-squared distribution as given in (34), where T is accumulated component-hours for the class and the statistic is evaluated at two degrees of freedom.

$$\mu_L = \frac{2T}{\chi^2_{\alpha}(2)} \quad (34)$$

The bound is computed separately for each component class rather than pooled across the installation, because the nine units are drawn from different failure-time distributions and a single exponential bound cannot legitimately be applied to a

heterogeneous population. Results are given in Table 6. Each bound is compared against the mean life $\eta\Gamma(1 + 1/\beta)$ rather than the characteristic life η , since for $\beta \neq 1$ the two differ. These bounds, between 0.042 and 0.167 years, lie far below any plausible mean life, so they would be satisfied by almost any prior and have no power to discriminate between parameter values. In addition, (34) is an exponential bound, whereas the three wear-out classes are modelled as Weibull with shape parameters up to 3.0, so for those classes the bound is only an approximation. The operational record therefore corroborates nothing at this exposure. No parameter is estimated from it, and no claim of empirical support is made anywhere in this paper

Table 6 Class-specific zero-failure lower confidence bounds at the 95% level, compared with the prior mean lives. (reported for completeness; at this exposure the bounds do not discriminate between priors).

Component class	Units	Exposure (component-h)	Lower bound (h)	Lower bound (yr)	Prior mean life (yr)
PV module	4	4,380	1,462	0.167	22.57
DC cabling / SPD	1	1,095	366	0.042	33.33
Tubular battery	2	2,190	731	0.083	5.80
Hybrid inverter	1	1,095	366	0.042	10.63
AC distribution	1	1,095	366	0.042	50.00

E. Observational Requirements for Parameter Identification

It is worth stating precisely how much observation would be required to replace these priors with estimates, because the answer bears on how the results should be used. Zero-failure data yield only a lower bound, and that bound grows linearly with exposure. To raise the battery-class bound to the mean life implied by its own prior would require approximately 8.7 years of uninterrupted failure-free operation of both units; for the inverter the corresponding figure is 31.9 years. These figures use the exponential bound of (34) and are therefore approximate for the Weibull classes. Extending observation at a single site does not resolve the problem either, because the probability of the system producing even one failure event remains below 10% after a full year and reaches only 44% after three years.

Parameter identification for this class of system is therefore a fleet problem rather than a duration problem. One site observed for twelve months yields 0.09 expected failure events; fifty sites yield 4.6 and one hundred sites yield 9.2, with a 95% probability of at least five events. This is consistent with the approach taken by Aitio & Howey (2021), who estimated battery end of life from fleet field data rather than from any single installation. The framework presented here is constructed so that such estimates, when available, can be substituted for the priors without any structural change to the model.

VII. RESULTS AND DISCUSSION

The framework of Sections III to VI is applied here to the case study installation. Results are presented in the order the

analysis proceeds: component reliability first, then availability under the default schedule, then the robustness of that schedule to the parameters carrying the greatest uncertainty, then the Markov and Monte Carlo checks, the cash-flow exposure and the economic interpretation, and finally a joint uncertainty analysis in which the uncertain inputs are varied together. All reliability, availability and optimisation results were computed in MATLAB and independently re-implemented in Python. The two implementations agree to the precision quoted on every component and system availability, every optimal interval, the cost decomposition, the sensitivity indices and the Markov steady-state vector. The Monte Carlo estimate of Section VII-G, the regret analysis of Table 11, the discounted cost metrics of Table 16 and the joint uncertainty analysis of Section VII-J were computed in Python only.

A. Component and System Reliability

Reliability functions for the five component classes and for the system as a whole are shown in Figure 3 over a twenty-year horizon, computed without preventive intervention so that the underlying failure behaviour is visible. The exponential components decline most gently, retaining reliabilities of 0.55 and 0.67 at twenty years for the direct current and alternating current assemblies respectively. The photovoltaic modules retain 0.49 at twenty years. This is attributable principally to their long characteristic life of twenty-five years rather than to the shape parameter, since a value of 1.5 denotes an increasing hazard rate and therefore accelerating rather than decelerating wear. Reliability at twenty years is a survival probability and is a distinct quantity from power degradation, with which it should not be conflated.

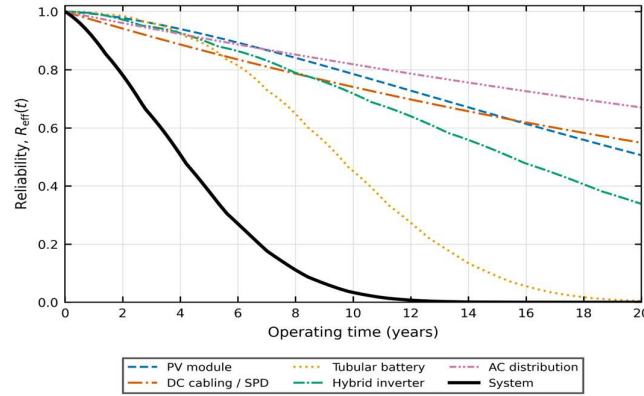


Figure 3 Reliability functions of the five component classes and of the system over a twenty-year horizon.

The hybrid inverter declines moderately, reaching 0.063 at the end of the horizon. The tubular battery exhibits by far the steepest wear-out, its reliability falling below 0.5 at 5.75 years and approaching zero by year twelve. System reliability is the product of the component functions raised to their series multiplicities, and falls below 0.5 at approximately 4.5 years. This compounding is the direct consequence of the series architecture of Section III-D, and it establishes the central engineering point: in an installation without redundancy the reliability of the whole is governed by the least reliable element and degraded further by every additional element in the path. Preventive maintenance is the only mechanism available to hold availability at a usable level.

B. Operational Availability Under the Default Schedule

Evaluating the model with the default maintenance regime, annual servicing of the modules and inverter, quarterly servicing of the battery bank, annual inspection of both distribution assemblies, and replacement of each component on reaching its nominal service life, gives a system operational availability of 0.99630. This corresponds to 32.4 hours of unavailability per year. Total annual ownership cost under this

schedule is ₦220,687, of which ₦214,209 is maintenance and replacement expenditure and ₦6,478 is the monetised value of unserved energy caused by component outages only; unserved energy caused by low irradiance, battery depletion or demand above system capacity is outside the model (Section IV-A). The default schedule is not a strawman: quarterly battery servicing is the interval most commonly recommended by Nigerian installers for flooded tubular cells, and annual servicing of the remaining subsystems reflects conventional manufacturer guidance.

Component availabilities at the optimised schedule derived in Section VII-C are shown in Figure 4 and tabulated in Table 7, together with the expected renewal cycle of each class. The tubular battery is the limiting element at 0.99943 per unit, and contributes twice because two units sit in series. The gap between the smallest component availability and the system availability arises from series compounding of corrective downtime and from planned and routine outages, which are subtracted once at system level as described in Section III-D. The quarterly routine outages of the battery bank remain the largest single contributor to planned downtime.

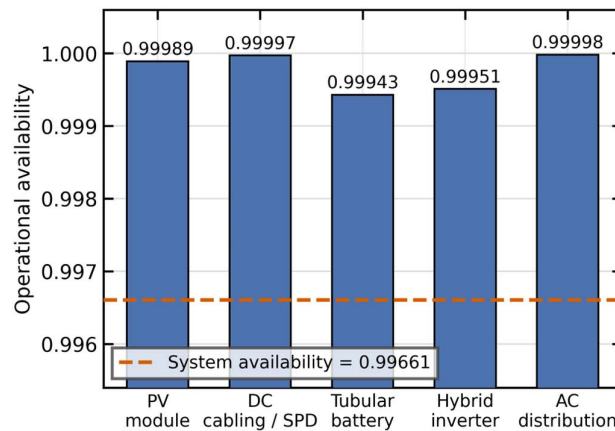


Figure 4: Operational availability of each component class at the cost-optimal schedule.

Table 7 Per-unit and block operational availability at the cost-optimal schedule, with expected renewal cycle length.

Component class	Units in series	Per-unit availability (corrective Outage only)	Block availability	Expected renewal c (yr)
PV module	4	0.99989	0.99957	21.53
DC cabling / SPD	1	0.99997	0.99997	33.33
Tubular battery	2	0.99943	0.99886	9.63
Hybrid inverter	1	0.99951	0.99951	16.77
AC distribution	1	0.99998	0.99998	50.00
Planned and routine maintenance	-	-	0.99871	-
System overall	-	-	0.99661	-

C. Cost-Optimal Imperfect Maintenance Schedule

The optimisation problem of Section V was solved by the separable decomposition described in Section V-C. To confirm that the decomposition does not distort the result, the problem was also solved jointly over all classes with the system-level unavailability coupling retained. The joint search returned a battery service interval of 17.1 months against 16.9 from the decomposition, and a total annual cost lower by ₦4.37, or 0.003%. The cost surface is therefore extremely flat in the neighbourhood of the optimum, and the replacement limit is not identified by the data. For the battery, $N = 19$ and $N = 25$ differ in annual cost by less than one part in nine thousand, and the value $N = 40$ returned for the modules and the inverter is the upper bound of the search in (30) rather than an interior optimum. The outcome is therefore reported as no planned replacement within the 25-year design life: at the optimised

intervals the planned replacement age $N \cdot T$ is about 40 years for the modules, 35 years for the battery and 106 years for the inverter. The intervals should be read as model-derived estimates, resolved to about a month under the adopted priors, and not as field-validated recommendations. The replacement limits are not identified by the data, as explained below. The resulting policy is given in Table 8. The battery bank is serviced every 16.9 months and the inverter every 31.9 months. The photovoltaic module cleaning interval is not optimised against reliability at all but held at its conventional annual value, and only the replacement limit of that class is optimised. This is the correct treatment given an improvement factor of 0.90: washing and visual inspection do not reverse encapsulant or interconnect ageing, so module cleaning is governed by soiling loss and energy yield rather than by failure behaviour, and optimising it against an availability objective would be meaningless.

Table 8: Default and cost-optimal maintenance policy for each component class.

Component class	Default interval	Optimal interval	Planned replacement	Improvement factor	Status
PV module	12.0 months	12.0 months (fixed)	None within design life ($N = 0.90$ 40*, $N \cdot T = 40$ yr)	-	Fixed, soiling-driven
DC cabling / SPD	12.0 months	12.0 months	Not applicable	-	Fixed, exponential
Tubular battery	3.0 months	16.9 months	None within design life ($N = 0.40$ $N \cdot T \approx 35$ yr)	-	Optimised
Hybrid inverter	12.0 months	31.9 months	None within design life ($N = 0.30$ 40*, $N \cdot T \approx 106$ yr)	-	Optimised
AC distribution	12.0 months	12.0 months	Not applicable	-	Fixed, exponential

In table 8, Default replacement limits correspond to nominal service lives of 25 years for the modules, 7 years for the battery bank and 12 years for the inverter. Upper bound of the search in (30). N is not identified by the data (Section VII-C). The largest departure from current practice concerns the battery, whose major service interval extends from quarterly to 16.9 months. This requires careful interpretation. The 16.9-month figure applies to the scheduled major service, comprising capacity testing, full equalisation charging and replacement of individually degraded cells. It is not a licence to leave flooded tubular batteries untouched for that period.

Routine tasks, distilled water top-up, terminal cleaning and greasing, remain quarterly throughout and enter the model explicitly, both as a fixed annual charge of ₦8,000 and as four separate one-hour outages per year in the availability calculation. Neglecting them would invalidate the characteristic life assumed in Table 4 and drive the optimum toward much shorter intervals.

The behaviour of annual cost with respect to the battery service interval is shown in panel (a) of Figure 5, and exhibits the characteristic asymmetric minimum of the maintenance-scheduling problem. To the left of the optimum, cost is

dominated by the expense of excessive servicing. To the right, failure-driven replacement and the unavailability penalty dominate. Panel (b) shows the corresponding availability, whose maximum lies at a different interval from the cost

minimum. The two objectives are not identical, and an operator whose priority is uptime rather than lifetime cost should schedule differently.

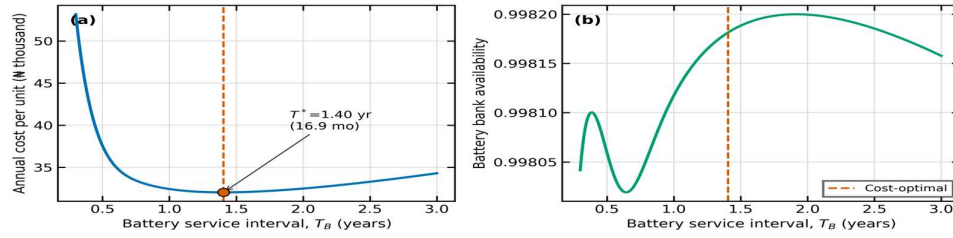


Figure 5: Total annual cost (a) and battery operational availability (b) as functions of the battery service interval.

The annual cost decomposition under both policies is given in Table 9 and shown in Figure 6. Optimisation reduces total annual cost from ₦220,687 to ₦145,617, a saving of ₦75,071 or 34.0%, while reducing expected annual unavailability from 32.4 to 29.7 hours. The saving is essentially the elimination of planned replacement rather than a reduction in servicing frequency. The scheduled-replacement term falls by ₦97,992, which is 130.5% of the net saving of ₦75,071; the reductions in scheduled servicing (₦33,339) and unserved energy (₦530) are largely offset by a ₦56,790 rise in failure-driven replacement. Under the optimised policy the planned

replacement age $N \cdot T$ is about 35 years for the battery, 106 years for the inverter and 40 years for the modules, all beyond the 25-year design life, so the replacement limit never binds and, as Table 15 confirms, virtually every battery renewal is failure-driven. The optimised policy is therefore, in effect, periodic imperfect servicing with run-to-failure renewal. This is the economically correct trade for this installation, because the cost of a planned replacement is only marginally below that of an unplanned one, so there is little value in pre-empting failure and considerable value in avoiding servicing that does not extend life.

Table 9: Annual cost decomposition under the default and cost-optimal policies.

Cost component	Default (₦/yr)	Optimal (₦/yr)	Change (₦/yr)
Scheduled service	53,826	20,488	-33,339
Failure-driven replacement	50,376	107,166	+56,790
Scheduled replacement	102,007	4,015	-97,992
Routine battery maintenance	8,000	8,000	0
Unserved energy (VOLL) from component outage	6,478	5,948	-530
Total	220,687	145,617	-75,071

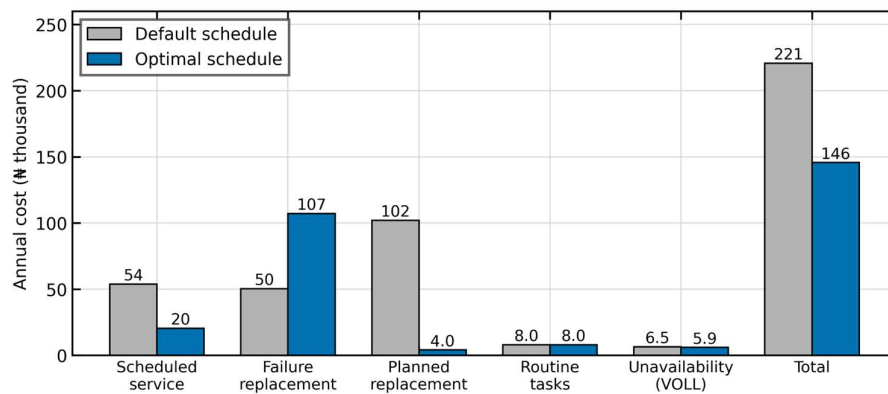


Figure 6: Annual cost decomposition under the default and cost-optimal policies.

It is worth stating plainly what this decomposition reveals about the original formulation of this problem. A classical age-replacement treatment, in which the preventive action is

assumed to renew the component completely, would charge the low cost of a service while crediting the full benefit of a replacement. Under such a formulation the model omits end-

of-life replacement expenditure entirely and consequently overstates both the achievable availability and the proportional saving. The imperfect-maintenance formulation adopted here removes that inconsistency by separating the cost of servicing from the cost of renewal and by allowing the service to restore only the fraction of accumulated age that it physically can.

D. Sensitivity to the Improvement Factor

The improvement factor q is the parameter introduced by the imperfect-maintenance formulation and is the least well determined input in the model, since no measurement of it exists for this installation. Its influence was therefore examined across the full admissible range from zero, corresponding to perfect renewal, to unity, corresponding to a service that removes no accumulated age at all. Results are shown in Figure 7 and given in Table 10. Total annual cost rises monotonically from ₦95,703 at $q = 0$ to ₦181,208 at $q = 1.0$, and system availability falls monotonically from 0.99764 to 0.99600, as expected: a service that removes less

accumulated age leaves the component older, so failures arrive sooner. The optimal battery service interval is not monotonic. It falls from 23.7 months at $q = 0$ to 15.4 months at $q = 0.2$ and then rises to 36.0 months at $q = 1.0$. Two effects oppose each other. At $q = 0$ each service renews the battery completely, so its age never exceeds one interval and stays in the low-hazard region of a Weibull distribution with $\beta = 3.0$, where each service removes age that carries little risk. For small positive q , virtual age drifts upward from one interval to the next into the steep part of the hazard, so removing age is worth more and more frequent servicing pays for itself. As q approaches unity each service removes little age, its value falls, and the optimum lengthens again. The reversal is a genuine feature of the model rather than an artifact of a flat cost surface: at $q = 0$, servicing every 15.4 months costs ₦3,175 (3.3%) more per year than the 23.7-month optimum. The optimal interval reaches its minimum of 15.3 months at $q = 0.1$.

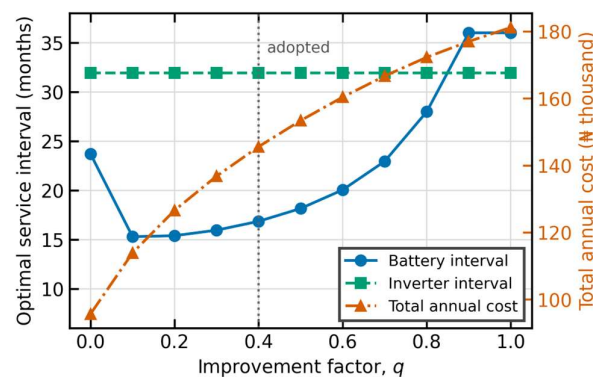


Figure 7 Optimal battery service interval and total annual cost as functions of the improvement factor q .

Table 10 Optimal policy and resulting cost as a function of the improvement factor.

Improvement factor q	Battery interval (months)	Replacement limit N	Inverter interval (months)	System availability	Total annual cost (₦)
0.0	23.7	40	31.9	0.99764	95,703
0.1	15.3	40	31.9	0.99719	113,902
0.2	15.4	40	31.9	0.99695	126,619
0.4	16.9	25	31.9	0.99661	147,617
0.6	20.1	16	31.9	0.99635	160,415
0.8	28.0	9	31.9	0.99615	172,310
1.0	36.0	6	31.9	0.99600	181,208

The bound of the search in (30) is 40 and indicates that no planned replacement occurs within the design life. Sensitivity of the optimal interval to q is not by itself sufficient to judge whether the recommendation is usable, because what matters to an operator is not how far the optimum moves but how much it costs to be at the wrong point. That question is answered by the regret analysis of Table 11, which evaluates the cost of following the recommended interval when the true

improvement factor differs from the adopted value. Across the range $q = 0.2$ to $q = 0.6$, which brackets any plausible description of an equalisation and cell-substitution service, following the recommendation costs at most 0.22% more than the schedule that would be optimal had q been known exactly. Even at $q = 0.8$ the penalty is 1.14%, and only at $q = 1.0$, where the service is assumed to remove no age at all, does it reach 3.44%

Table 11 Cost of following the recommended service interval when the true improvement factor differs from the adopted value.

True q	Optimal interval (months)	Cost at that optimum (₦/unit/yr)	Cost at recommended interval	Regret
0.2	15.4	22,839	22,872	0.15 %
0.3	16.0	27,780	27,791	0.04 %
0.4	16.9	32,035	32,035	0.00 %
0.5	18.2	35,812	35,830	0.05 %
0.6	20.1	39,208	39,293	0.22 %
0.8	28.0	44,984	45,496	1.14 %
1.0	36.0	49,301	50,996	3.44 %

This distinction matters and resolves what would otherwise be a serious weakness. The optimal interval is sensitive to q , but the decision is not, because the cost function is flat in the neighbourhood of its minimum. An operator adopting the recommended interval without any measurement of service effectiveness forfeits a fraction of 1% of battery ownership cost across the entire plausible range of q . The value of measuring q therefore lies not in improving the schedule, which it would barely change, but in confirming that the service being performed is effective at all: the penalty rises sharply only as q approaches unity, which is the regime in which the service is not working.

Two things follow, and these two things must be separated. The total cost of ownership is strongly dependent on q and almost doubles over the range of admissible values for q , so information about q is important for predicting the cost of running the system. The one that is not dependent on q is the penalty for using the recommended interval instead of the optimum interval, which would have been used if q had been known, not the level of the cost. The second is that the qualitative conclusions are valid for all values in the range. The battery remains the component whose servicing interval matters most, the optimal interval remains far longer than the quarterly practice currently followed, and optimisation delivers a substantial saving throughout, ranging from 25.5% at $q = 1.0$ to 55.6% at $q = 0$, against a default policy evaluated at the same improvement factor. The value of 0.40 adopted for the battery reflects a service that removes rather more than half of accumulated age, which is consistent with equalisation and selective cell replacement but not with top-up alone.

A second assumption warrants the same treatment. The cost of a failure-driven replacement exceeds that of a planned one by only 4% to 6% in Table 5, because the dominant term in both is the price of the component itself and the additional downtime is priced separately through the availability term. A reviewer may reasonably object that emergency procurement in a market with import lead times should carry a larger premium. The optimisation was therefore repeated with uniform premiums of 15%, 30%, 50% and 80%, and at each level the default policy was re-evaluated at the same premium, so that the saving is a like-for-like comparison. The sweep applies a single uniform premium to every class, whereas the premiums implied by Table 5 are component-specific at 3.7%, 4.7% and 5.6% for the battery, PV module and inverter respectively, so the base case is the starting point of the sweep rather than one of its uniform steps. Results are given in Table 12.

As the premium rises to 80%, the optimal battery service interval shortens from 16.9 to 12.2 months and the replacement limit falls from 25 to 10, so the planned replacement age falls to about 10.2 years, while system availability varies by less than 0.0004. The saving relative to the default policy falls from 34.0% to 16.7%. The size of the saving therefore depends directly on the assumed failure premium, and the base-case figure should be read as conditional on the small premiums of Table 5. The qualitative conclusions hold across the range: the optimal interval remains longer than quarterly practice and the battery remains the governing component.

Table 12 Optimal policy and saving as a function of the failure premium, with the default policy evaluated at the same premium.

Failure premium	Optimal battery interval (months)	N	Planned replacement age N·T (yr)	Default cost (₦/yr)	Optimal cost (₦/yr)	Saving (%)
Table 5 values (3.7% to 5.6%)	16.9	25	35.1	220,687	145,617	34.0
15%	16.0	15	20.1	225,541	156,377	30.7
30%	14.9	12	14.9	232,517	171,001	26.5
50%	13.3	11	12.2	241,818	188,986	21.8
80%	12.2	10	10.2	255,769	213,043	16.7

E. Parameter Sensitivity and Robustness to the Value of Lost Load

Normalised sensitivity indices are shown in Figure 8 and the five largest are given in Table 13. The battery mean time to repair and characteristic life dominate, with indices of -0.001138 and 0.001119 respectively. A 10% change in either alters system availability by approximately 0.0114% of its current value under the local linear approximation. All magnitudes are small in absolute terms because the system operates in a high-availability regime, where small relative parameter changes produce small absolute availability changes.

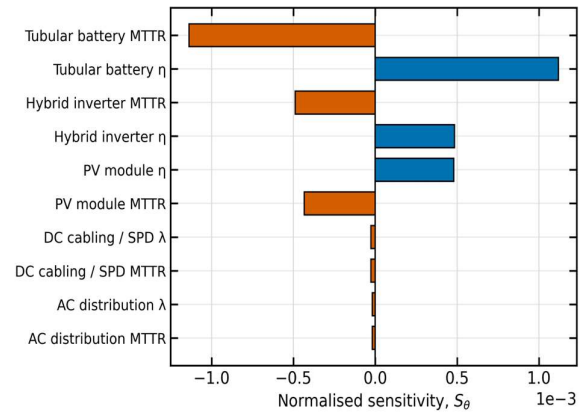


Figure 8: Normalised sensitivity of system availability to each component parameter.

Table 13: Five parameters with the largest influence on system availability.

Rank	Parameter	Sensitivity	10% change gives	Direction
1	Tubular battery MTTR	-0.001138	-0.0114%	Negative
2	Tubular battery η	0.001119	0.0112%	Positive
3	Hybrid inverter MTTR	-0.000490	-0.0049%	Negative
4	Hybrid inverter η	0.000485	0.0048%	Positive
5	PV module η	0.000479	0.0048%	Positive

The exponential failure rates of the two distribution assemblies do not appear in the leading group. This indicates that availability in this installation is governed principally by wear-out rather than by random external events. It should not be read as implying statistical independence from those events or the absence of any influence: a low sensitivity index indicates limited local influence at the operating point, nothing more. The practical reading is that investment in battery longevity and in shortening battery repair turnaround yields a better return than any intervention on the distribution subsystems.

The value of lost load was varied across the range ₦200 to ₦1,500 per kilowatt-hour, a 7.5-fold span comfortably exceeding the spread reported in willingness-to-pay studies for sub-Saharan African residential consumers. Results are shown in Figure 9. Under the joint optimisation, the battery service interval moves only from 17.0 to 17.5 months and system availability remains at 0.9966 across the entire range, while total annual cost rises from ₦142,047 to ₦157,474 as the higher valuation is applied to almost the same physical downtime. The recommendation therefore does not depend on resolving the value of lost load precisely, because the optimum is determined by the ratio of servicing to replacement cost and by the shape of the hazard, both better constrained than the value of lost load. Because the demand E_a enters (28) only through the product $VOLL \cdot E_a$, a $\pm 20\%$ error in the estimated demand is equivalent to a value of lost load of ₦400 to ₦600 per kilowatt-hour, which lies well inside the range examined, so the optimal policy is also invariant to the demand estimate.

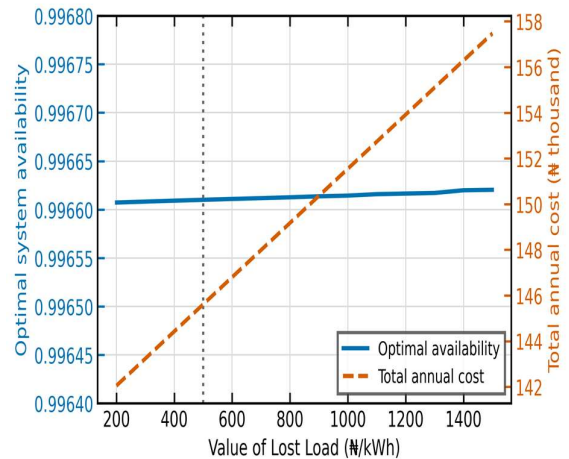


Figure 9: Optimal system availability and total annual cost as functions of the assumed value of lost load.

F. Markov Cross-Check

The battery component was solved independently as a three-state continuous-time Markov chain over the operational, corrective-repair and preventive-maintenance states. At the optimal service interval the steady-state probability vector is 0.99881 for the operational state, 0.00094 for corrective repair and 0.00024 for preventive maintenance. The comparison with the renewal-theoretic result is given in

Table 14. The two differ, and that difference should be reported as such rather than presented as agreement.

Table 14 Markov steady-state probability vector for the tubular battery, compared with the renewal-theoretic result.

Quantity	Value	Interpretation
Operational state probability	0.99881	Markov operational availability
Corrective repair state	0.00094	Fraction of time under corrective repair
Preventive maintenance state	0.00024	Fraction of time under scheduled service
Renewal-theoretic availability (per unit 0.99921		Primary method, scheduled service included
Difference	0.00039	Attributable to the approximations in Section VI

Two distinct approximations separate the two formulations, and both act in the same direction. The Markov generator requires a constant transition rate and therefore substitutes an exponential approximation for the Weibull hazard, which cannot represent the pre-emption of wear-out failures achieved by servicing well before the characteristic life. Separately, representing preventive maintenance by a transition rate equal to the reciprocal of the service interval makes the time between services exponentially distributed with that mean, whereas the policy of Section IV schedules the service deterministically at a fixed age. The Markov model therefore approximates both the failure process and the maintenance policy and is used here to confirm the order of magnitude and the internal consistency of the transition structure rather than as an independent numerical validation.

G. Monte Carlo Check

A discrete-event Monte Carlo simulation provides an independent check on the analytical result. Component failure times were sampled from their Weibull and exponential distributions, the virtual-age service policy was applied, planned and routine outages were imposed once per class visit as in 12, and the fraction of system uptime was accumulated over a ten-year horizon for ten thousand independent system histories. In an earlier version, every component started the horizon as new, which biases availability upward because the wear-out components spend the window in their low-hazard early phase; with that initialisation the estimate levelled off near 0.9960 over horizons of 20 to 80 years instead of approaching the analytical value. Each history is therefore now started in steady state by simulating and discarding a warm-up period of 200 years, which is equivalent to drawing the initial age, virtual age and position in the service cycle of each component from the stationary age distribution of its renewal process. The distribution of simulated availabilities is shown in Figure 10.

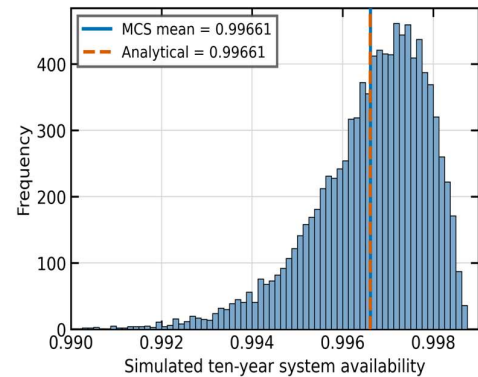


Figure 10: Distribution of simulated ten-year system availability across ten thousand independent histories under the cost-optimal policy.

The simulated mean availability is 0.99661, with a 95% confidence interval of [0.99659, 0.99664], against the analytical value of 0.99661. The analytical value lies within the confidence interval and agrees with the simulated mean to five decimal places, so the discrete-event simulation corroborates the analytical result. The agreement also confirms that the steady-state initialisation removes the upward bias present in the earlier new-component formulation.

H. Cash-Flow Exposure of the Optimised Policy

The saving reported in Section VII-C is an expected annual figure, and expectation is not the only thing a household cares about. The optimised policy achieves part of its saving by allowing components to run closer to failure, which converts predictable scheduled expenditure into unpredictable unscheduled expenditure. Because the objective function is risk-neutral, that conversion is invisible in the headline number and must be reported separately. The expected frequency of unplanned replacement events under each policy is given in Table 15.

Table 15 Expected frequency of unplanned replacement events under the default and optimised policies.

Component class	Cost per event (₦)	Default (events/yr)	Optimal (events/yr)	Default return period (yr)	Optimal return period (yr)
PV module	155,000	0.138	0.159	7.2	6.3
Tubular battery	280,000	0.059	0.208	17.1	4.8
Hybrid inverter	380,000	0.028	0.060	35.3	16.8
All classes	-	0.225	0.426	4.4	2.3
Events above ₦250,000	-	0.087	0.267	11.5	3.7

The consequence is material and should not be buried. Under the default policy the probability of at least one unplanned replacement in a given year is 20.2%, and the probability of an event costing more than ₦250,000 is 8.3%, corresponding to one such event every 11.5 years. Under the optimised policy those figures rise to 34.7% and 23.5% respectively, and the return period for a large event falls to 3.7 years. A household on the income typical of this installation may find a ₦280,000 battery replacement arriving unannounced every four years harder to absorb than a smaller but predictable annual servicing bill, even though the expected annual cost is lower by a third.

Three practical responses follow, and the choice between them belongs to the household rather than to the model. The saving may be set aside as a sinking fund, in which case the optimised policy is straightforwardly better because the fund accumulates faster than the shocks arrive. The schedule may be shortened toward the default, trading expected cost for predictability, and the flatness of the cost surface documented in Section VII-C means a substantial move in that direction is inexpensive. Or the replacement limits may be reduced so that more renewals are planned rather than failure-driven, which raises expected cost but restores predictability. A formal treatment would replace the risk-neutral objective with a mean-variance or conditional-value-at-risk criterion, and that is identified in Section VIII as a worthwhile extension.

I. Economic Interpretation

The annual saving of ₦75,071 accumulates to approximately ₦1,876,775 over a 25 years design life on an undiscounted basis. The present value of that stream falls as the discount rate rises and the undiscounted figure should not be quoted as though it were rate-independent. Expressed on a per-unit-energy basis, the installation delivers 3,504 multiplied by system availability, approximately 3,492 kilowatt-hours annually. Two metrics are reported in Table 15. The first is a conventional levelised cost comprising capital and maintenance expenditure only. The second adds the monetised value of unserved energy caused by component outage and is designated, the extended economic cost, since the value of lost load is an opportunity cost borne by the household rather than a generation expenditure and should not be conflated with one.

The levelised cost is computed as the sum of capital expenditure and the discounted stream of maintenance expenditure, divided by the discounted stream of delivered energy, with $C_{cap} = ₦1,644,000$, annual maintenance expenditure of ₦139,669 excluding the value of lost load, annual delivered energy of 3,492 kWh, and a study period of twenty-five years. At a zero discount rate this gives $(1,644,000 + 25 \times 139,669) / (25 \times 3,492) = ₦58.83/\text{kWh}$. Capital recovery accounts for ₦65,760 of the annualised total, which is why the levelised figures exceed the annual maintenance costs of Table 9.

Table 16 Levelised cost of energy and extended economic cost under both policies, over a twenty-five year design life.

Discount rate	LCOE, optimal (₦/kWh)	Extended cost, optimal (₦/kWh)	LCOE, default (₦/kWh)	Reduction
0 %	58.83	60.53	80.20	26.6 %
5 %	73.40	75.10	94.77	22.6 %
10 %	91.86	93.56	113.24	18.9 %
15 %	112.82	114.53	134.21	15.9 %

Both denominators are based on energy demanded rather than on a full generation model, and therefore neglect conversion efficiency, usable depth of discharge, solar resource variability and long-term module degradation. They should be read as ownership-cost indicators rather than as physically complete generation costs. The reduction achieved by

optimisation is not constant across discount rates, falling from 26.6% undiscounted to 15.9% at 15%, because the capital term is fixed while the maintenance stream on which the saving acts is discounted. The levelised figures scale inversely with the estimated demand, so a $\pm 20\%$ error in demand moves the optimised LCOE at a zero discount rate from ₦58.83 to

between ₦49.02 and ₦73.53 per kWh, while the percentage reduction achieved by optimisation is unchanged.

These values exceed the prevailing residential tariff of the local distribution company at every discount rate, and no claim is made that the installation competes directly with grid supply on cost. That comparison is in any case not the relevant one. Grid supply is unavailable at this site, and the realistic alternative is petrol self-generation at well above ₦1,000 per kilowatt-hour. Against that alternative the system remains economic by a wide margin at every discount rate considered, and optimised maintenance improves the position further.

The results consistently identify the tubular battery as the component governing both availability and cost under the adopted parameter assumptions. It has the steepest hazard, the two largest sensitivity indices, the shortest optimal service interval and the largest single contribution to total annual cost. This ordering differs from the pattern reported across the grid-connected literature reviewed in Section II-B, where the inverter is repeatedly identified as the dominant contributor to unavailability, but it should not be read as an independent finding. With a battery characteristic life of 6.5 years against 12 years for the inverter in a series structure, no other ordering is arithmetically possible. The more informative result is the crossover. Holding all other inputs fixed, the inverter becomes the limiting element only if the battery characteristic life exceeds 15.0 years, corresponding to a reference life of 24.3 years at 25 °C, and the battery remains limiting in 99.7% of the joint uncertainty samples of Section VII-J. Because flooded

tubular batteries at the site temperature are unlikely to reach this life (15.0 years), storage is expected to remain the governing element in comparable off-grid installations, and reliability conclusions from grid-tied studies should be re-examined before they are transferred to off-grid residential design. When planned and routine outages are included, the battery class remains limiting for any characteristic life up to 40 years, because its planned major-service and quarterly routine outages alone exceed the total unavailability of the inverter.

J. Joint Parameter Uncertainty Analysis

The analyses of Sections VII-D and VII-E vary one input at a time while holding the others fixed, and so cannot show how uncertainties interact. A joint Monte Carlo uncertainty analysis was therefore performed. A total of 2,000 parameter sets were drawn by Latin hypercube sampling from the distributions in Table 17, which cover the Weibull shape and characteristic life of the three wear-out classes, the constant failure rates of the two distribution assemblies, the mean times to repair, the maintenance cost parameters and failure premium, the site enclosure temperature through the acceleration factor of (32), the value of lost load, the annual energy demand and the improvement factors. The inputs were sampled independently. For each set the default policy was evaluated and the optimisation of Section V was repeated, so that each sample yields its own optimal intervals, availability, annual cost and saving. The results are summarised in Table 18 as the median and the 5th and 95th percentiles.

Table 17 Uncertain inputs sampled in the joint uncertainty analysis.

Parameter	Base value	Distribution	Sampled range
Battery reference characteristic life at 25 °C	10.6 yr	Uniform	8.5 to 12.7 yr
Inverter reference characteristic life at 25 °C	19.5 yr	Uniform	15.6 to 23.4 yr
Site enclosure temperature (sets AF in Eq. 32)	32 °C	Uniform	29 to 35 °C
PV module characteristic life	25 yr	Uniform	20 to 30 yr
Battery shape parameter β	3.0	Uniform	2.0 to 4.0
Inverter shape parameter β	2.0	Uniform	1.5 to 2.5
PV module shape parameter β	1.5	Uniform	1.2 to 2.0
DC and AC failure rates λ	0.030 and 0.020 per yr	Log-uniform	0.5 to 3 times base
MTTR, all classes	Table 4	Uniform multiplier	0.5 to 2 times base
Service cost C_s	Table 5	Uniform multiplier	0.7 to 1.5 times base
Component price (scales C_e and C_r together)	Table 5	Uniform multiplier	0.8 to 1.3 times base
Failure premium of C_e over C_r	3.7% to 5.6%	Uniform	3% to 30%
Value of lost load	₦500/kWh	Triangular	₦200 to ₦1,500/kWh, mode ₦500
Annual demand E_a	3,504 kWh	Uniform	2,803 to 4,205 kWh ($\pm 20\%$)
Battery improvement factor	0.40	Uniform	0.2 to 0.6
Inverter improvement factor	0.30	Uniform	0.1 to 0.5
PV module improvement factor	0.90	Uniform	0.8 to 1.0

Table 18: Results of the joint uncertainty analysis (2,000 samples).

Output	Base case	Median	5th percentile	95th percentile
Optimal battery interval (months)	16.9	16.4	11.3	23.9
Optimal inverter interval (months)	31.9	31.5	21.2	47.4
System availability, default policy	0.99630	0.99601	0.99461	0.99674
System availability, optimised policy	0.99661	0.99609	0.99424	0.99753
Annual cost, default policy (₦)	220,687	248,394	200,027	299,836
Annual cost, optimised policy (₦)	145,617	170,189	128,901	232,960
Saving relative to default (%)	34.0	30.4	19.1	41.4
LCOE, optimised, 0% discount (₦/kWh)	58.83	65.04	49.52	87.86

The optimal battery service interval lies between 11.3 and 23.9 months in 90% of samples, and the inverter interval between 21.2 and 47.4 months. System availability under the optimised policy lies between 0.9942 and 0.9975, and total annual cost between ₦128,901 and ₦232,960. The saving relative to the default policy is positive in 100% of samples, with a 90% range of 19.1% to 41.4%. The battery remains the limiting element in 99.7% of samples. Spearman rank correlation identifies site temperature, battery reference life, service cost as the inputs contributing most to the spread of the battery interval, and component price, site temperature as the main contributors to the spread of annual cost. The single-point values reported elsewhere in this paper should therefore be read as central estimates within these ranges rather than as precise predictions.

VIII. LIMITATIONS

Seven limitations bear on how these results should be read, and they are stated in order of how much they constrain the conclusions. The first concerns what the availability figure represents. The quantity computed here is technical availability, the long-run fraction of time for which every component of the energy path is functional and not withdrawn for maintenance. It is not service availability. An off-grid system can fail to serve load while fully functional, through insufficient irradiance across consecutive overcast days, depletion of battery state of charge, demand exceeding instantaneous generation and storage capacity, or conversion losses. The value of lost load term in the objective therefore prices only the unserved energy caused by component outage, not the total loss-of-load cost of the installation. Technical availability is an upper bound on service availability, and the true loss-of-load probability is necessarily higher than one minus the value reported here.

The second is the improvement factor. The imperfect-maintenance formulation adopted in Section IV resolves the inconsistency inherent in applying age-replacement mathematics to servicing actions that do not renew a component, but it does so at the cost of introducing a parameter for which no measurement exists at this installation. Section VII-D quantifies the consequence: the recommended battery interval ranges from 15.4 months at $q = 0.2$ to 36.0 months at $q = 1.0$, and is 23.7 months at $q = 0$. Measuring service effectiveness, by tracking capacity recovery after equalisation across a population of banks, is the single most valuable refinement available to this work.

Third, every reliability parameter in Table 4 is a literature-derived prior rather than a field estimate, and Section VI-E established that the observational evidence required to displace

those priors cannot be obtained from a single installation on any practical timescale. This is a limitation of the empirical claim rather than of the framework, and it is the reason the contribution is stated as a transferable method with declared priors rather than as a measurement of Nigerian residential reliability. Users applying this framework elsewhere should substitute their own parameters and should not treat Table 4 as established fact. The temperature-acceleration argument of Section VI-B rests on a rule of thumb documented for lead-acid cells and electrolytic capacitors and applied here to complete assemblies, which is an extrapolation beyond the scope of the supporting sources.

Fourth, the study addresses a single installation, and generalisation to sites with markedly different climate, load profile or installation quality would require a multi-site study. Fifth, the photovoltaic modules are treated as failure-time entities rather than as progressively degrading power sources, so the annual power losses of 1% or more reported in the tropical degradation literature are not captured. A coupled reliability-degradation model would represent the contribution of declining module output to effective unavailability and would improve the cost estimates of Table 15. Sixth, the series reliability block diagram assumes independent failures; common-cause mechanisms are discussed in Section III-D but not modelled, so the reported availability is optimistic to that extent. Seventh, the objective function of Section V is risk-neutral: it minimises expected annual cost and is indifferent to the variance of that cost. Section VII-H shows that the optimised policy attains part of its saving by accepting a threefold increase in the frequency of large unplanned replacements, an exposure a household on this income may not be able to absorb. Replacing the expectation with a mean-variance or conditional-value-at-risk criterion would let the trade-off between expected cost and cash-flow predictability be selected explicitly rather than left implicit, and is the most directly useful economic extension of this work.

IX. CONCLUSION

This paper has developed a framework for availability assessment and cost-optimal maintenance scheduling of residential off-grid photovoltaic systems, and applied it to a 4.2 kVA installation at the University of Ilorin staff quarters in Nigeria. The framework combines component-level Weibull and exponential failure-time modelling, series reliability block diagram aggregation, and imperfect preventive maintenance optimisation under a Kijima Type I virtual-age model in which a scheduled service restores only the fraction of accumulated age that it physically can. Unavailability is valued against an annual energy demand estimated from the household load

inventory, and end-of-life replacement expenditure is carried explicitly, both of which are necessary for the cost accounting to close.

Three principal results follow, all of which are model-derived estimates under literature-derived priors rather than field-validated findings. Optimisation of the maintenance policy raises technical availability from 0.99630 to 0.99661, equivalent to a reduction in expected annual unavailability from 32.4 to 29.7 hours, and reduces expected annual ownership cost from ₦220,687 to ₦145,617, a saving of 34.0% requiring no additional up-front investment. The saving comes mainly from removing planned replacement rather than from servicing less often: the scheduled-replacement cost falls by ₦97,992, more than the net saving, because the replacement limit is not reached within the design life and almost every battery renewal becomes failure-driven. Section VII-H shows that this raises the frequency of unplanned replacement events, which matters for a household that cannot absorb a lump-sum shock. The estimated cost-optimal major service interval is 16.9 months for the tubular battery bank (90% range 11.3 to 23.9 months under joint parameter uncertainty) and 31.9 months for the hybrid inverter (21.2 to 47.4 months), with the two constant-failure-rate assemblies retained on annual inspection and the photovoltaic modules serviced for energy-yield rather than reliability reasons. The battery interval applies to the scheduled major service and does not displace the quarterly routine tasks, which are carried in the model as a fixed annual charge and as four separate outages per year.

The second result concerns robustness. The optimal policy is invariant across a 7.5-fold range in the value of lost load and across a $\pm 20\%$ error in the estimated demand. When the default policy is evaluated at the same failure premium, the saving falls from 34.0% at the Table 5 premiums to 16.7% at an 80% premium, so its size is conditional on the small premiums adopted. The optimal battery interval is sensitive to the improvement factor, but following the recommended interval costs at most 0.22% more than the true optimum for q between 0.2 and 0.6. The third result concerns which component governs availability. With a battery characteristic life of 6.5 years against 12 years for the inverter, the battery necessarily governs availability and cost in this series system; this is a consequence of the adopted inputs rather than an independent finding, and the ordering reverses only if the battery characteristic life exceeds 15.0 years. Reliability conclusions from grid-tied studies should therefore be re-examined before they are transferred to off-grid residential design.

The boundaries of the contribution are stated plainly. The availability computed is technical rather than service availability, so energy adequacy is outside its scope, and the value of lost load term prices only unserved energy caused by component outage, not the total loss-of-load cost of the household. All reliability parameters are literature-derived priors, and the analysis quantifies what would be required to displace them: approximately 8.7 years of failure-free operation to constrain the battery class at a single site, or a fleet of the order of one hundred installations observed for twelve months. Parameter identification for this class of system is a fleet problem rather than a duration problem, and the framework is constructed so that fleet-derived estimates can be

substituted without structural change. Coupled reliability-degradation modelling, measurement of service effectiveness, loss-of-load simulation incorporating irradiance and state of charge, and a multi-site study spanning Nigerian climatic zones are the most useful directions for further work.

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AUTHOR CONTRIBUTIONS

A. O. Abdulsemiu: Conceptualization, Investigation, Writing-original draft, Methodology, Formal analysis, Software, Data curation, Project administration and editing. **A. O. Otuoz:** Investigation, Supervision, Resources, Data curation, review and editing.

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