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A Data-Driven, Survey-Based Bottom-Up Load Modeling and Optimization Framework for Hybrid Renewable Energy Systems in Standalone Microgrids

Adrian L. Rey

Polytechnic University of the Philippines

Ginno L. Andres

Polytechnic University of the Philippines

Arvin R. De la Cruz

Polytechnic University of the Philippines

Abstract: The precise configuration of standalone hybrid renewable microgrid systems in remote regions is frequently obstructed by a critical lack of historical consumption data. This paper introduces a mathematically rigorous, data-driven framework that bridges this "information gap" by merging bottom-up, appliance-level load modeling with stochastic Monte Carlo simulations. In contrast to conventional top-down modeling, which frequently results in inefficient over-capitalization or compromised energy reliability, this research adopts an approach that captures the inherent stochasticity of both human behavior and environmental fluctuations. By leveraging scenario-driven stochastic optimization grounded in a 95th-percentile (P95) design benchmark, the study identifies an optimal configuration of 1,000 kWp in solar PV capacity coupled with an 800 kWh battery storage system. This specific architecture is engineered to sustain grid stability even during protracted multi-day solar deficits within the project zone. From a techno-economic perspective, the system achieves a leveled cost of energy between \$0.17 to \$0.52 per kWh and a substantial 87% reduction in carbon footprint. Ultimately, this framework offers a transferable and scalable model for implementing sustainable power solutions in data-limited regions globally.

Keywords: Microgrid, Optimal sizing, Renewable energy, Load modeling

Introduction

The global shift toward decentralized energy systems has positioned standalone microgrids as a primary mechanism for achieving universal energy access in isolated and islanded communities (Lassalle & Martínez, 2021; Vera et al., 2022). However, the successful implementation of these systems is often compromised by a fundamental lack of prior demand data (Sayani et al., 2022). When engineers rely on aggregated regional benchmarks (top-down estimation), they frequently miss the nuanced, stochastic usage patterns of rural households (Alahmed & Al-Muhaini, 2021; Dosa et al., 2025). This misalignment typically results in "sizing mismatches," where the system is either prohibitively expensive due to over-engineering or unreliable due to under-capacity (Qiu & Entchev, 2024; Sayani et al., 2022).

Recent advancements in the field emphasize that high renewable penetration (exceeding 90%) is only attainable through granular, bottom-up modeling that captures specific appliance-level behaviors (Alahmed & Al-Muhaini, 2021; Qiu & Entchev, 2024; Rajbhandari et al., 2023). Furthermore, the dual uncertainty of weather-dependent generation and unpredictable user demand requires a transition from rigid deterministic models to scenario-

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based stochastic optimization (Antoniadou-Plytaria et al., 2022; Cabrera-Tobar et al., 2022; Takam & Fruiba, 2025). This study fills a critical gap in contemporary research by presenting a six-stage methodology that integrates on-site ethnographic data with advanced probabilistic analytics to optimize both technical reliability and economic feasibility (Farhadi & Iqbal, 2024).

Method

The proposed framework utilizes a structured, sequential workflow designed to eliminate the guesswork from remote microgrid design. Fig. 1 presents the proposed six-stage methodology for data-driven microgrid sizing.



Figure 1. Proposed six-stage methodology for data-driven microgrid sizing

The survey data collection successfully captured appliance-level usage patterns from 119 responses across 383 fields, including 84 appliance-related fields. Survey data includes appliance ownership, rated wattage, quantity, and hourly usage patterns for residential, commercial, and institutional loads.

Bottom-Up Data Acquisition: Primary demand data were gathered through on-site household surveys, capturing detailed inventories of appliances, rated power, and daily usage cycles (Sayani et al., 2022). Utilization factors were applied per hour to each appliance category to reflect realistic daily peaks, particularly the evening residential surges common in off-grid settings (Lassalle & Martínez, 2021).

Diversity Factor Application: To avoid the trap of coincidence peak overestimation, a diversity factor was applied to the total connected load, ensuring the system is sized for realistic simultaneous usage (Yamegueu et al., 2024).

Probabilistic Scenario Simulation: Thousands of potential demand and solar irradiance scenarios were generated using Monte Carlo simulations (Cabrera-Tobar et al., 2022; Ghasemi et al., 2022). K-means clustering was then utilized for scenario reduction to maintain computational efficiency while preserving real-world variability (Pothireddy & Vuddanti, 2024).

Techno-Economic Multi-Objective Optimization: System sizing for the PV arrays, battery energy storage systems, and diesel backup was conducted to minimize both the Net Present Cost and carbon emissions (Farhadi and Iqbal, 2024; Maoulida et al., 2025; Zhu et al., 2022).

Uncertainty Assessment: Sensitivity analysis was performed to test the system's resilience against exogenous variables like fuel price shocks and varying annual demand growth rates (Barnes et al., 2022; Maoulida et al., 2025).

The study was conducted in the Municipality of Agutaya, located in the Province of Palawan, Philippines, selected due to its critical need for a sustainable microgrid system. The specific site of interest is the island village of Concepcion, which faces ongoing challenges in achieving reliable and efficient energy access. Table 1 shows the techno-economic input parameters used for hybrid PV–diesel–battery system modeling and optimization.

To establish a robust framework for system sizing and performance optimization, an annual electrical consumption of 1,615,123 kWh was defined as the primary load baseline. The financial architecture of the solar photovoltaic array includes an initial capital investment of PHP 65,000 per kW and an annual operational and maintenance allocation of PHP 1,400 per kW. Given the site's average solar irradiance of 4.39 kWh/kWp/day, the high resource potential reinforces the economic and technical feasibility of large-scale PV integration in this context.

Conversely, the diesel generation component exhibits a distinct cost profile, requiring a lower upfront expenditure of PHP 28,000 per kW but incurring higher variable operating costs of PHP 2.5 per kWh plus fixed O&M fees. This disparity underscores a fundamental trade-off: while diesel units offer lower entry costs, their long-term operational burdens often outweigh the higher initial investment required for renewable alternatives. Table 2 shows the mathematical equations utilized for the calculations.

Table 1. Techno-economic input parameters

Parameter	Unit	Value
Project Lifetime	Years	20
Discount Rate	%	9.0
Annual Load Growth	%/year	4.0
Initial Load Demand	kWh/year	1,615,123
PV Capital Cost	PHP/kW	65,000
PV O&M Cost	PHP/kW/year	1,400
Solar Irradiance	kWh/kWp/day	4.39
Diesel CAPEX	PHP/kW	28,000
Diesel OPEX (Variable)	PHP/kWh	2.5
Diesel OPEX (Fixed)	PHP/kW/year	300
Fuel Consumption Rate	L/kWh	0.30
Diesel Fuel Price	PHP/L	65
Fuel Price Escalation	%/year	3.0
Battery CAPEX	PHP/kWh	27,000
Battery O&M Cost	PHP/kWh/year	405
Battery Efficiency	%	90
Depth of Discharge	%	80
Battery Lifetime	Years	10
System Losses	%	5.0
Stability Factor	% of Load	40

Table 2. Mathematical equations for load modeling and optimization.

Eq.	Equation	Variables / Description
(1)	$P_{i,t} = N_i \cdot P_i^{\text{rated}} \cdot U_{i,t}$	$P_{i,t}$: power of appliance i at time t (kW); N_i : number of units; P_i^{rated} : rated power (kW); $U_{i,t}$: utilization factor
(2)	$P_t^{\text{total}} = \sum P_{i,t}$	P_t^{total} : total load (kW); n : number of appliance types
(3)	$E_{\text{annual}} = \sum (P_t^{\text{total}} \cdot \Delta t)$	E_{annual} : annual energy (kWh); Δt : time step (h)
(4)	$P_{\text{max,div}} = P_{\text{connected}} / DF$	$P_{\text{connected}}$: connected load (kW); DF : diversity factor
(5)	$X^{(k)} \sim f_x(x)$	$X^{(k)}$: random sample; $f_x(x)$: probability distribution
(6)	$E[P_i] = (1/N) \sum P_i^{(k)}$	$E[P_i]$: expected load; N : number of simulations
(7)	$P_i^{\text{p95}} = \text{Percentile}_{95}(P_i^{(k)})$	P_i^{p95} : 95th percentile load
(8)	$E^{\text{PV}} = P^{\text{PV}} \cdot H \cdot PR$	P^{PV} : PV capacity (kW); H : irradiance (kWh/kWp/day); PR : performance ratio
(9)	$F = \alpha E^{\text{DG}} + \beta P^{\text{DG,Grated}}$	F : fuel consumption (L); α, β : coefficients
(10)	$E^{\text{DG}} = \sum (P^{\text{DG}}_{i,t} \cdot \Delta t)$	$P^{\text{DG}}_{i,t}$: diesel power (kW)
(11)	$\text{SOC}_t = \text{SOC}_{t-1} + (\eta_{\text{ch}} \cdot P_{\text{ch},t} - P_{\text{dis},t} / \eta_{\text{dis}}) / E_{\text{bat}}$	SOC_t : state of charge; $\eta_{\text{ch}}/\eta_{\text{dis}}$: efficiencies; E_{bat} : battery capacity
(12)	$\text{SOC}_{\text{min}} \leq \text{SOC}_t \leq \text{SOC}_{\text{max}}$	SOC limits
(13)	$\text{DOD} = 1 - \text{SOC}_{\text{min}}$	Depth of discharge
(14)	$P^{\text{PV}}_{i,t} + P^{\text{DG}}_{i,t} + P_{\text{dis},t} = P_{\text{load},t} + P_{\text{ch},t} + P_{\text{loss},t}$	Power balance
(15)	$\text{NPC} = \sum [C_i / (1+r)^i]$	NPC: net present cost; C_i : cost; r : discount rate
(16)	$\text{LCOE} = \sum [C_i / (1+r)^i] / \sum [E_i / (1+r)^i]$	LCOE: cost per kWh
(17)	$\text{CO}_2 = E_{\text{diesel}} \cdot F$	E_{diesel} : emission factor
(18)	$\min (w_1 \cdot \text{NPC} + w_2 \cdot \text{CO}_2)$	w_1, w_2 : weighting factors
(19)	$\text{REF} = E^{\text{PV}} / E_{\text{total}}$	Renewable fraction
(20)	$S = (\Delta \text{Output} / \text{Output}) / (\Delta \text{Input} / \text{Input})$	Sensitivity index
(21)	$P_{\text{supply},t} \geq P_{\text{load},t}^{\text{p95}}$	Reliability constraint

Results and Discussion

The synthesized load curves highlight a substantial evening peak, a characteristic stress point for battery storage in isolated microgrids (Lassalle and Martínez, 2021). Fig. 2 shows the result of the stochastic bottom-up load profile for the study area in year 5.

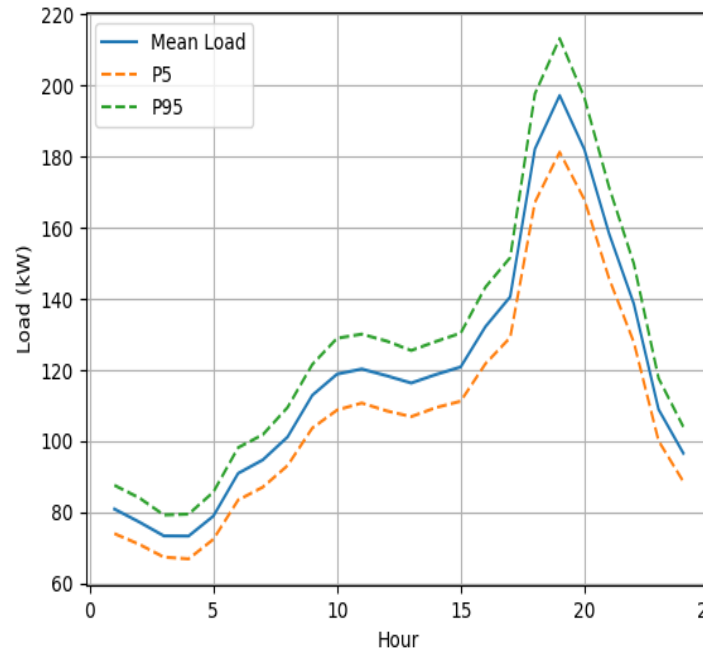


Figure 2. Daily load profile comparison: deterministic vs. stochastic (year 5)

The Monte Carlo simulation results for the Year 5 load profile illustrate the expected daily demand pattern along with its associated uncertainty. The mean curve represents the most probable load behavior, showing a gradual increase from early morning values of around 80 kW to a pronounced evening peak approaching 200 kW. This peak typically occurs between hours 18 and 19, reflecting higher consumption during nighttime activities.

The difference between the 5th (P5) and 95th (P95) percentiles provides a clear metric for quantifying load volatility, which is fundamentally tied to the daily demand cycle. While this interval remains relatively tight during low-utilization periods, it undergoes a marked expansion as the system approaches its peak, signifying a drop in predictive certainty during high-load scenarios. This correlation suggests that the grid is most susceptible to forecasting errors precisely when operational pressure is at its maximum. Consequently, the observed divergence in these probabilistic bounds underscores the necessity for maintaining robust reserve margins to buffer against unforeseen consumption surges.

The results confirm that initial demand forecasting errors are not linear; even small inaccuracies can lead to disproportionately high operational costs if the system relies too heavily on diesel backup (Sayani et al., 2022; Yamegueu et al., 2024). By adopting the P95 load profile, a standard ensuring the system meets demand in 95% of all simulated scenarios, the framework provides a robust "safety buffer" against unexpected surges and solar intermittency (Antoniadou-Plytaria et al., 2022; Melamu & Orumwense, 2025).

In the primary case study, an optimized 1,000 kWp solar PV and 800 kWh battery energy storage system configuration significantly outperformed traditional deterministic models. Specifically, the stochastic approach accounted for extended periods of low solar radiation that deterministic models typically ignore, thereby reducing the required operational run-time of carbon-intensive diesel generators (Rangel et al., 2023; Yamegueu et al., 2024). Economic viability was scrutinized over a 20-year project lifecycle using LCOE modeling (Elmouatamid et al., 2024; Farhadi and Iqbal, 2024). The year 5 load profile was employed during the optimization phase to ensure that the proposed system is capable of meeting the projected future energy demand of the study area.

Environmentally, the transition to this optimized hybrid configuration achieved a significant reduction in carbon intensity. While initial capital investment remains higher than diesel-only setups due to storage costs, the near 90% reduction in lifetime fuel consumption provides a strategic hedge against the extreme price volatility of global oil markets (Clairand et al., 2021; Rangel et al., 2023).

Technical assessments of the battery energy storage system components showed that while the levelized cost of energy (LCOE) is relatively stable across minor technical fluctuations, the environmental performance (CO₂ emissions) is highly sensitive to round-trip charging efficiency (Zhu et al., 2022, 2024). This underscores the necessity for future research studies to prioritize high-efficiency storage technologies, as battery losses directly correlate with increased diesel backup run-time (Moosavi et al., 2025; Zhu et al., 2024). Table 3 shows the summary of optimization results for the Hybrid PV–Diesel–Battery microgrid system.

Table 3. Summary of optimization results for the hybrid PV–diesel–battery system

Parameter	Unit	Value
Gross Annual Consumption	kWh/year	1,615,123
PV Capacity	kW	1,000
Battery Capacity	kWh	800
Diesel Capacity	kW	500
PV Generation	kWh/year	1,603,080
Diesel Generation	kWh/year	796,400
Battery Throughput	kWh/year	451,231.6
Fuel Consumption	L/year	268,378.4
LCOE	PHP/kWh	28.37
Renewable Energy Share	%	50

The optimization results demonstrate that the proposed hybrid energy system effectively meets the projected Year 5 demand profile. Analysis of the data indicates that the system supports an annual consumption of approximately 1.62 GWh, with a balanced contribution from both renewable and conventional sources. Notably, the installed 1,000 kW solar PV system generates approximately 1.60 GWh annually, accounting for a substantial portion of the total energy requirement and closely aligning with the overall demand.

To ensure reliability during peak and low solar periods, the system is complemented by an 800 kWh battery storage and a 500 kW diesel generator. Despite the presence of diesel backup, fuel usage remains relatively controlled at around 268,000 liters per year, indicating a strong reliance on renewable energy. The battery also plays a critical role, with a throughput exceeding 451 MWh annually, helping smooth fluctuations and enhance system stability.

Conclusion

This study demonstrates that the synthesis of bottom-up behavioral granularity and stochastic optimization offers a significantly more reliable foundation for microgrid design than traditional top-down estimation. By utilizing Monte Carlo simulations and a P95 design standard, we can ensure system resilience in the face of both demand and resource uncertainty. The findings validate that these integrated frameworks are not only cost-competitive, with LCOE values as low as \$0.17/kWh, but also essential for achieving the carbon reduction targets required for sustainable rural electrification.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest.

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Author(s) Information

Adrian L. Rey

Polytechnic University of the Philippines
A. Mabini Campus, Anonas Street, Sta. Mesa, Manila, 1016
Metro Manila, Philippines.
Contact e-mail: enr.adrianrey@gmail.com
ORCID iD: <https://orcid.org/0009-0004-0993-742X>

Ginno L. Andres

Polytechnic University of the Philippines
A. Mabini Campus, Anonas Street, Sta. Mesa, Manila, 1016
Metro Manila, Philippines.
ORCID iD: <https://orcid.org/0009-0002-9491-5406>

Arvin R. De la Cruz

Polytechnic University of the Philippines
A. Mabini Campus, Anonas Street, Sta. Mesa, Manila, 1016
Metro Manila, Philippines.
ORCID iD: <https://orcid.org/0000-0001-7325-5301>

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