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Topography-Informed Techno-Economic Sizing of Hybrid PV-Battery Systems for MSMEs in East Java: A Comparative Solar-Resource and Productive-Load Assessment

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ABSTRACT

Battery size was more sensitive to when micro, small, and medium enterprises (MSMEs) use electricity than to which of the six nearby East Java cities they are located in. This study develops a reproducible pre-feasibility framework for Madiun, Jember, Bangkalan, Lamongan, Surabaya, and Malang by linking a protocol-based structured narrative review with Global Solar Atlas data, reconstructed hourly PV profiles, a representative 60 kWh/day productive load, chronological PV-battery dispatch, exhaustive capacity search, life-cycle costing, and sensitivity analysis. Under a renewable-fraction constraint of at least 90%, five sites selected a 16 kWp PV/25 kWh battery, while lower-yield Bangkalan required 17 kWp PV. The central finding was operational: shifting 8 kWh/day (13.3% of demand) from evening to solar hours reduced the optimal battery size from 25 to 20 kWh and lowered the levelized cost by about 10%, whereas the inter-city solar resource spread changed the optimal PV array by only 1 kWp. Thus, demand chronology can provide greater design leverage than modest geographic resource differences. Because solar profiles were modeled and reconstructed, weather was deterministic, and one generic load was used, the results are screening decision rules rather than procurement specifications.

1. Introduction

Micro, small, and medium enterprises are major contributors to employment, household income, and local value creation in Indonesia. Their electricity demand is often modest compared with industrial facilities. Still, it is operationally critical because refrigeration, pumping, milling, welding, food processing, digital services, and lighting directly determine daily output and product quality. In East Java, the concentration of enterprises across metropolitan, coastal, agricultural, and elevated

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inland areas means that electricity costs, outage exposure, roof conditions, and renewable energy potential vary substantially. The provincial profile of micro and small industries, therefore, supports the need for energy solutions that can be deployed incrementally and adapted to heterogeneous business activities [1].

Hybrid PV-battery systems are attractive for this context because PV can offset daytime consumption. At the same time, batteries can transfer energy to evening production, smooth short irradiance fluctuations, and provide limited outage support. However, a battery does not compensate for poor design. Oversized storage raises capital costs and replacement risk, whereas undersized storage leads to deep cycling, unmet demand, and continued dependence on diesel or a weak grid. The design problem is consequently multi-dimensional: PV output depends on irradiance, orientation, temperature, soiling, humidity, and cloud cover; storage performance depends on depth of discharge, efficiency, temperature, and aging; and economic performance depends on load timing, financing, backup cost, and policy conditions [2-6].

East Java is particularly suitable for a location-sensitive comparison. Madiun and Lamongan have strong annual solar resources; Surabaya and Bangkalan are hot coastal lowlands; Jember is a humid inland center; and Malang is a cooler, elevated city. Long-term solar averages are useful for screening, but regional evidence shows that tropical irradiance can vary strongly over short time scales and across relatively short distances. Ihsan *et al*. [7] reported high spatial and temporal heterogeneity around the equator and highlands, while Ramli *et al*. [8] demonstrated in Surabaya that dust, rain, partial cloud, temperature, and humidity can materially reduce instantaneous PV output. A uniform kWp-per-kWh rule can therefore hide differences in energy yield, seasonal reserve needs, and maintenance requirements.

Optimization studies offer several ways to address these interacting factors. HOMER-type chronological simulation is widely used for screening hybrid energy systems. At the same time, particle swarm optimization (PSO), genetic algorithms, NSGA-II, and multi-criteria decision-making methods can search larger design spaces or balance cost, reliability, emissions, and social criteria [9-15]. Indonesian case studies have shown that locally selected components and dispatch assumptions affect renewable fraction and cost of energy in Ponorogo and West Papua [16-17]. Productive-use research also indicates that system economics improve when energy-consuming activities are scheduled during periods of renewable generation rather than treated as inflexible demand [18-19].

The central gap is not a lack of hybrid-system models, but a lack of transparent MSME-scale comparisons that isolate two design levers under the same assumptions: exogenous geographic resource differences and endogenous load timing. Recent synthesis indicates that decentralized renewable energy can improve MSME productivity and operational continuity, while realized financial benefits remain strongly context-dependent [20]. The unresolved question for East Java is therefore whether nearby microclimates or operational rescheduling has the larger effect on equipment size. This study tests the counterintuitive proposition that moving a modest share of productive demand into solar hours can reduce required storage more than selecting a nominally higher-yield city. It aims to: (i) synthesize evidence on microclimate, optimization, productive use, and implementation; (ii) quantify site-level solar and PV-yield differences across six East Java locations; (iii) identify least-cost PV-battery configurations under a common renewable-fraction constraint; (iv) evaluate solar-aligned productive-load scheduling; and (v) derive implementation rules and explicit inference limits. The contribution is a reproducible pre-feasibility framework that separates the PV-sizing effect of location from the battery-sizing effect of load chronology.

2. Literature Review

2.1 Microclimate, Topography, and PV Performance

PV energy production is governed first by the solar resource incident on the module plane and then by conversion losses. De Soto *et al*. [2] formalized the relationship between irradiance, cell temperature, and module electrical output. At the same time, Duffie and Beckman [4] established the foundations of solar geometry and energy balance used in most engineering models. In practical systems, global horizontal irradiation (GHI) indicates the resource on a horizontal surface, global tilted irradiation (GTI) represents the resource available to a fixed-tilt array, and specific PV yield converts these resources into annual AC energy per installed kWp. Because MSME installations commonly use constrained roofs and simple fixed structures, site-specific GTI, tilt, shading, and orientation are more actionable than provincial-average GHI alone. A recent standalone PV assessment in Malang likewise showed that orientation and tracking choices materially alter modeled output, reinforcing the need to treat array geometry as a site-level input [21].

Temperature reduces the crystalline-silicon module voltage and, therefore, the power at otherwise similar irradiance. The review by Skoplaki and Palyvos [3] showed that temperature coefficients should be included in performance estimates, particularly in warm climates. Indonesian experiments reinforce this concern. Amrizal *et al*. [22] evaluated PV thermal management behavior under tropical conditions, and Kunaifi *et al*. [23] reported performance ratios of around 0.81 for polycrystalline systems operating in a tropical rainforest climate, alongside technology-dependent degradation. These findings suggest that a hot coastal site may require better rear ventilation and thermal spacing even when its annual irradiance is favorable.

Cloud cover, humidity, aerosols, and rainfall introduce variability that annual totals cannot capture. Ramli *et al*. [8] observed that two weeks of dust accumulation reduced PV power by 10.8% in their Surabaya experiment; rainy and cloudy conditions produced reductions exceeding 40% and 45%, respectively, during the observed events. Ihsan *et al*. [7] similarly found large spatial and temporal heterogeneity in irradiance across the Asia-Pacific region, with greater variability near the equator and in the highlands. The implication for battery design is important: a monthly average may correctly approximate annual energy yet understate the depth and duration of low-generation sequences that determine backup dependence and state-of-charge stress.

Topography affects PV-battery design both directly and indirectly. Elevation generally lowers ambient temperature but can coincide with orographic cloud formation; coastal locations may receive strong direct radiation but face salt corrosion, heat, and urban aerosols; agricultural lowlands can experience dust and biomass-related soiling; and dense urban roofs can experience shading and elevated surface temperatures. The appropriate design response is therefore not necessarily a different technology at every site, but a location-specific combination of PV capacity, battery reserve, mounting, ventilation, cleaning frequency, and operational scheduling.

2.2 Hybrid PV-Battery Sizing and Optimization

Hybrid-system sizing is commonly formulated as a constrained optimization problem in which decision variables include PV capacity, battery energy, inverter capacity, generator capacity, and sometimes dispatch-control parameters. The objective may minimize net present cost or levelized cost of energy, while constraints limit unmet load, loss-of-power-supply probability, battery state of charge, emissions, and renewable fraction. Lambert *et al*. [9] described the chronological simulation logic used in HOMER, and Ridha *et al*. [12] reviewed the expansion of PV sizing into multi-objective and multi-criteria formulations.

Metaheuristic methods become attractive when the problem is non-linear, discontinuous, or contains many combinations of components. Kennedy and Eberhart [10] introduced PSO, and Wali *et al*. [13] applied it to economic sizing of PV-battery systems. Deb et al. [11] developed NSGA-II for multi-objective optimization, enabling designers to examine trade-offs rather than selecting a single minimum-cost solution. Kumar *et al*. [14] reviewed a broad range of hybrid-system sizing methods and concluded that the quality of the resource and load inputs can be as important as the search algorithm. Saib *et al*. [15] likewise emphasized that the selection of the optimization method should match the system structure, objective functions, and the level of uncertainty.

Advanced algorithms do not remove the need for transparency. A discrete grid search is computationally simple when there are only two main capacity variables and provides an auditable relationship between design choices and results. For a pre-feasibility study with PV and battery capacities tied to realistic MSME increments, an exhaustive evaluation avoids algorithm-specific convergence settings, making the results easier to reproduce. In a later engineering phase, the same chronological model can be embedded in PSO or NSGA-II to include inverter sizing, battery chemistry, tariffs, emissions, and stochastic weather years.

Indonesian studies demonstrate why local calibration is necessary. Xu *et al*. [16] used techno-economic and environmental analysis to compare hybrid combinations for Ponorogo, East Java, showing that the preferred configuration depends on resource conditions and component selection. Bawan *et al*. [17] developed an optimized hybrid system for rural electrification in West Papua and highlighted the importance of local demand, diesel displacement, and reliability. Recent tropical assessments in Malang and Sidoarjo likewise show that configuration and load context materially alter PV performance, energy yield, LCOE, and payback [24-25]. Huda *et al*. [26] and Khanal *et al*. [27] further showed that load type, electricity tariffs, and energy-sharing assumptions alter the economic optimum. These findings support a consistent multi-city comparison before applying a single regional design rule.

2.3 Productive Use, Load Timing, and MSME Viability

Productive-use integration changes the economics of distributed renewable energy because system value depends on when electricity is consumed, not only on annual demand. A load served directly by PV avoids battery conversion losses, reduces cycling, and can allow a smaller storage system. A load that occurs after sunset requires either storage or backup even when annual PV generation exceeds annual consumption. Aziz *et al*. [28] showed that energy management and dispatch strategies materially affect PV-diesel-battery performance, reinforcing the need to model chronology rather than annual energy balance alone.

Shafira *et al*. [18] found that integrating productive activities improved the utilization and financial performance of a hybrid renewable system in eastern Indonesia. For cold-chain applications, Nugraha *et al*. [19] reported that a hybrid configuration could reduce diesel use and emissions while achieving a payback period of approximately 4.4 years. A 2026 systematic review and meta-analysis of decentralized renewable energy for MSME clusters found a positive pooled effect on enterprise performance, but also substantial contextual heterogeneity and dominant financial barriers [20]. These findings are directly relevant to MSMEs engaged in fisheries, food processing, ice production, agricultural drying, and refrigeration. In such businesses, pre-cooling, pumping, defrost cycles, drying batches, and non-urgent processing can often be shifted toward the solar window without reducing daily output.

Load shifting is not cost-free or universally applicable. Production schedules, labor availability, hygiene requirements, cold-chain temperature limits, and customer delivery times constrain flexibility. A robust design should separate critical loads, which require a continuous supply, from deferrable loads, which can be rescheduled within a defined time window. This distinction improves the credibility of battery sizing and helps business owners understand which operational changes generate the modeled savings.

2.4 Data-Driven Forecasting, GIS, and Implementation Conditions

Long-term satellite data are valuable for spatial screening, but higher-resolution forecasting can improve operational control and uncertainty analysis. Pfenninger and Staffell [29] demonstrated the value of validated hourly reanalysis and satellite data for long-term PV patterns, while Gufron et al. [30] combined long short-term memory modeling with inverse-distance weighting for hourly solar-radiation estimation in tropical regions. Such approaches can be used to construct multiple weather years, quantify forecast error, and develop adaptive battery dispatch rather than relying on a single typical year.

Implementation conditions are equally important. IRENA [31] and NREL [32-33] show that PV and battery cost trajectories have improved, but local quotations can vary due to taxes, transport, engineering scope, financing, and replacement warranties. Indonesian rooftop-PV projects must also account for the quota and interconnection framework established by Ministerial Regulation No. 2/2024 [34]. For an MSME that requires resilience rather than export revenue, the business case should be based primarily on self-consumption, avoided backup cost, and continuity of productive operations.

Table 1
Literature synthesis and analytical positioning

Study	Context/method	Principal finding	Relevance to this study	Remaining limitation
Skoplaki and Palyvos [3]	Review of PV temperature-performance relationships	Higher module temperature reduces electrical efficiency	Supports temperature-aware site comparison	Does not address MSME load timing
Ihsan et al. [7]	Asia-Pacific satellite analysis of spatial and temporal irradiance variability	Equatorial and highland areas show substantial heterogeneity	Justifies localized East Java solar inputs	Regional analysis, not enterprise sizing
Kunaifi et al. [23]	Operational PV data across technologies and climates	Tropical systems showed technology-dependent PR and degradation	Provides a measured tropical benchmark	Different systems and countries
Ramli et al. [8]	Outdoor PV experiment in Surabaya	Dust, rain, humidity, and cloud caused large short-term losses	Highlights weather/soiling risk at an East Java site	Short experimental exposure
Xu et al. [16]	Hybrid-system analysis for Ponorogo, East Java	Resource and component choices changed the cost and renewable fraction	Confirms need for local configuration	Not focused on MSME productive loads
Shafira et al. [18]	A hybrid system integrated with productive activities in eastern Indonesia	Productive use improved utilization and economic outcomes	Supports load-timing scenario	Single-underserved-region case

Study	Context/method	Principal finding	Relevance to this study	Remaining limitation
Ridha et al. [12]	Review of PV optimization and MCDM	Multi-objective methods balance cost, reliability, and environmental criteria	Frames optimization choices	Review is not East Java-specific
Wali et al. [13]	PSO sizing of PV-battery hybrid system	PSO can identify economically sustainable capacities	Supports later algorithmic extension	The algorithm's result depends on the input quality
Kumar et al. [14]	Review of hybrid sizing methodologies	No single sizing method is universally superior	Supports transparent grid search for two variables	Limited operational MSME detail
Bawan et al. [17]	Optimized hybrid system for West Papua	Local resource, load, and diesel conditions determine the optimum	Indonesian evidence for localized design	The rural electrification scale differs
Gufron et al. [30]	LSTM-IDW tropical solar-radiation estimation	Data-driven estimation improves spatiotemporal resolution	Future pathway for stochastic/real-time sizing	Requires monitoring and model validation
Nugraha et al. [19]	Hybrid renewable energy for the Indonesian cold chain	Diesel and emission reductions with viable payback	Direct relevance to refrigeration MSMEs	Technology and tariff context may differ
Rizkita and Prasetyo [20]	Systematic review and meta-analysis of decentralized renewable energy for MSME clusters	DRE improves enterprise performance, but effects and financial viability are context-dependent	Strengthens the productive-use and MSME implementation rationale	High cross-context heterogeneity; not a site-specific sizing model
Prasetyo et al. [21]	PVsyst assessment of tilt and tracking for standalone PV in Malang	Array geometry materially changes the modeled energy output	Supports site-specific tilt and orientation inputs	Does not model MSME load chronology or storage

Table 1 shows that the literature is strong on individual mechanisms—temperature, cloud, optimization, productive use, and forecasting—but fragmented in its treatment of multi-city MSME sizing. The present study positions itself between a broad review and a detailed bankable design. It uses peer-reviewed evidence to define the mechanisms and limitations, and then applies a single consistent screening model across six local data sets. The conceptual relationship is summarized in Figure 1.

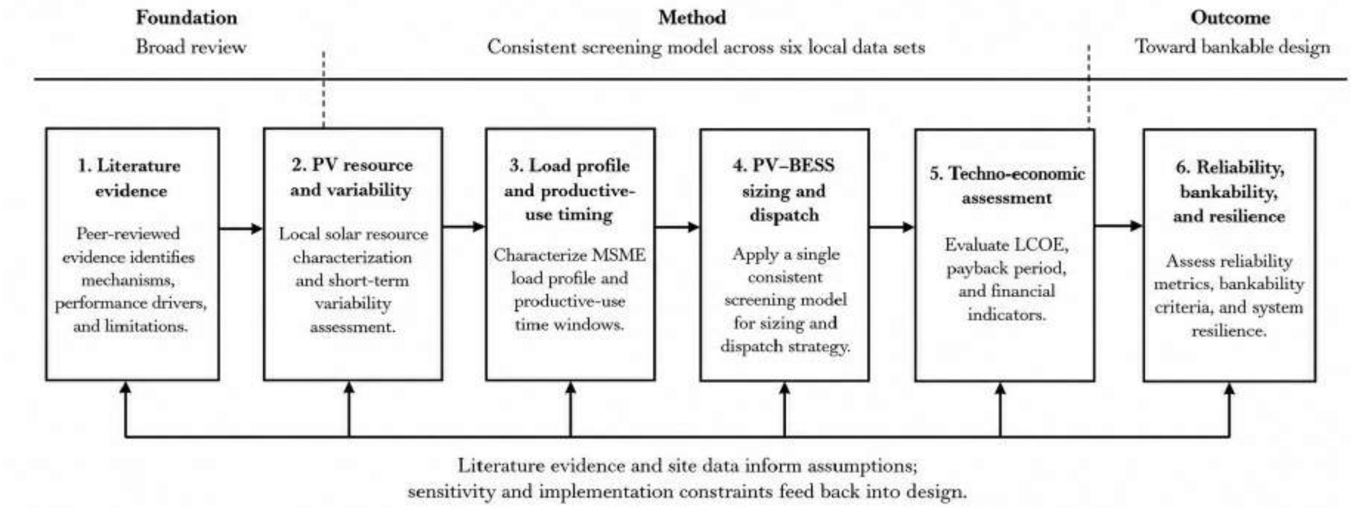

Fig. 1. Literature-grounded conceptual framework linking local conditions, load timing, sizing, and MSME outcomes

3. Methodology
3.1 Research Design and Data Sources

The research combined a protocol-based structured narrative review with a comparative techno-economic simulation. The review was not treated as a conventional descriptive background section; it was used to predefine mechanisms, modeling choices, performance metrics, and interpretation boundaries that were then traced into the quantitative model. The approach follows guidance that literature reviews should state their purpose, search and selection logic, data extraction, and synthesis procedure, even when they are not formal systematic reviews [35].

Review scope and source identification. The review covered five predefined domains: (i) tropical PV performance and microclimate; (ii) PV-battery sizing and reliability metrics; (iii) productive-use load timing; (iv) forecasting and spatial data; and (v) Indonesian implementation and financing conditions. The evidence base combined the manuscript's established peer-reviewed and authoritative technical sources with an updated set from the Scopus export dated 4 August 2026. References were verified against DOI or publisher metadata before inclusion.

Eligibility and charting. Sources were retained when they provided a directly usable mechanism, parameter, benchmark, or implementation constraint for the East Java MSME model. Records unrelated to energy-system design or MSME productive use, duplicates, and items with insufficient bibliographic traceability were excluded. For each retained source, the study context or method, principal finding, relevance to the present model, and remaining limitation were charted; representative entries are reported in Table 1.

Synthesis and distinction from a systematic review. Evidence was grouped thematically and translated into explicit model decisions: temperature and soiling informed interpretation of yield; chronological dispatch avoided annual-energy balancing; renewable fraction defined the screening constraint; productive-use evidence motivated the load-shifting scenario; and cost and financing evidence defined sensitivity ranges. The review is “structured” because its scope, eligibility logic, charting fields, themes, and model linkages are explicit and auditable. It differs from a formal systematic review because it does not claim exhaustive database coverage, a PRISMA flow, duplicate independent screening, risk-of-bias scoring, or meta-analysis.

The GSA resource is a long-term modeled data source prepared by Solargis for the World Bank Group and ESMAP [36-37]. It is suitable for comparative screening because the six sites are processed using a consistent methodology. It is not a substitute for a detailed site survey or bankable measurement campaign. The reports explicitly caution that the data are provided for general information and policy discussion; local shading, roof orientation, soiling, individual weather events, and financing commitments require additional verification.

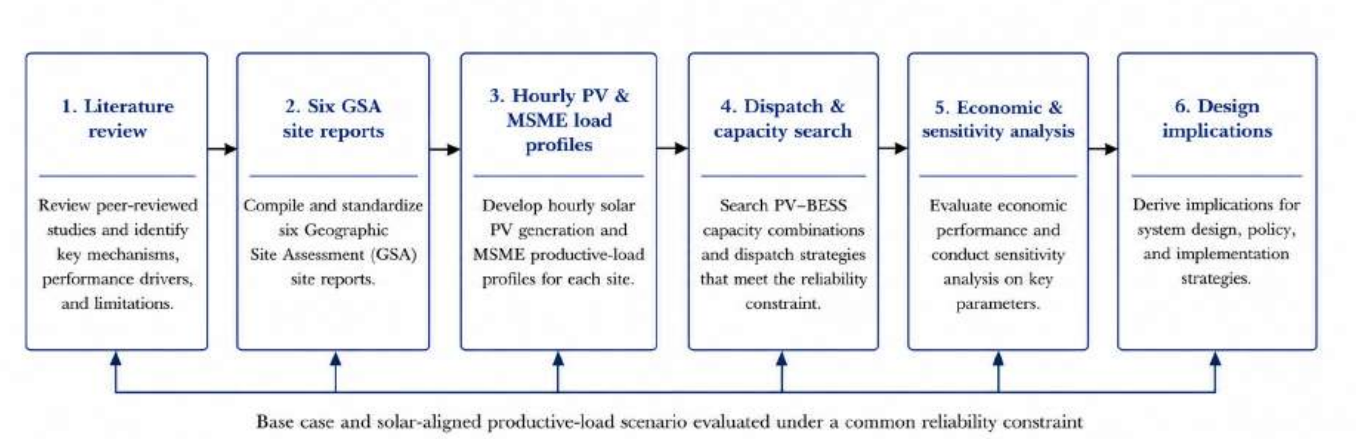

Fig. 2. Literature review, data processing, sizing, and techno-economic assessment workflow

Table 2
Site characteristics and annual solar-resource indicators (irradiation in kWh/m²/year) [37]

Site	Lat.	Long.	Elev. (m)	Temp. (°C)	GHI	DNI	DIF	GTI	Tilt (°)
Madiun	-7.6291	111.5169	68	25.9	1957.2	1413.5	914.5	1990.1	12
Jember	-8.1689	113.7022	91	25.3	1881.0	1438.9	834.2	1909.1	12
Bangkalan	-7.0295	112.7473	4	27.6	1860.1	1336.1	892.4	1887.4	11
Lamongan	-7.1204	112.4156	9	27.3	1950.6	1429.0	898.1	1983.5	12
Surabaya	-7.2463	112.7378	2	27.4	1952.0	1479.0	869.7	1988.9	12
Malang	-7.9771	112.6340	451	23.9	1867.6	1384.7	862.1	1897.5	12

3.2 PV Profile Reconstruction and MSME Load

The average hourly PV values on page 2 of each GSA report were summed to obtain a monthly average day, and the result was multiplied by the number of days in the corresponding calendar month. The resulting monthly totals reproduced the reported annual PV output to the precision of the rounding. For a candidate PV capacity P_PV, hourly generation was scaled linearly from the 12 kWp reference profile:

$$E_{\mathrm{PV},s,t} = \left(\frac{P_{\mathrm{PV}}}{12}\right) \times E_{\mathrm{GSA},s,t} \quad (1)$$

where $E_{\mathrm{PV},s,t}$ is the candidate-system energy at site s and hour t, and $E_{\mathrm{GSA},s,t}$ is the GSA reference-system energy. Linear scaling is appropriate for pre-feasibility screening when array orientation, inverter loading, and component efficiency are held constant. Detailed design should replace this assumption with module- and inverter-specific performance curves [2].

A representative food-processing and cold-storage enterprise was defined with an average demand of 60 kWh/day, equivalent to 21,900 kWh/year. The profile had a 4.2 kW peak and 71.3% of daily demand between 06:00 and 18:00. Daytime demand was for refrigeration, preparation, pumping, and processing; evening demand was for cold storage, lighting, digital equipment, and residual production. The profile is intentionally generic and serves as a controlled comparison across sites; it is not evidence that all MSMEs have the same demand chronology. The load-shifting result is therefore conditional on this profile and should be replaced by measured 15-minute data for a specific enterprise.

3.3 Battery Dispatch and Reliability Metrics

At every hourly time step, PV first supplied the concurrent load. Surplus energy charged the battery, subject to charge efficiency and the upper state-of-charge limit. When PV was insufficient, the battery discharged subject to the discharge efficiency and the minimum state-of-charge limit. Residual unmet demand was assigned to backup energy, representing a diesel generator, weak-grid purchase, or other firm supply. The simplified state transition was:

$$\mathrm{SOC}_t = \min\left[\mathrm{SOC}_{\max}, \mathrm{SOC}_{t-1} + \eta_c E_{\text{surplus},t} - \frac{E_{\text{deficit},t}}{\eta_d}\right] \tag{2}$$

The model used a 90% usable depth of discharge and a 90% round-trip efficiency. A critical-load autonomy indicator was also calculated by dividing usable battery energy by the energy required for a 2 kW critical load. This value is not whole-business autonomy; it represents the duration for which selected refrigeration, controls, communications, and essential lighting could be supported during an outage.

Renewable fraction was used as the screening reliability metric:

$$\mathrm{RF} = 1 - \frac{E_{\text{backup}}}{E_{\text{load}}} \tag{3}$$

Feasible configurations required RF ≥ 90%, equivalent to annual backup energy below 10% of demand. This metric captures annual dependence but not the duration or clustering of deficits, the state of charge at the start of an outage, or multi-day cloudy events. Because the weather input is deterministic and reconstructed from repeated average-day profiles, it may understate consecutive periods of low generation and battery stress. Loss-of-load probability and outage-hour simulation should therefore be added when measured weather and chronological outage records are available.

3.4 Capacity Search and Economic Model

A discrete exhaustive search evaluated PV capacities from 8 to 30 kWp in 1 kWp increments and battery capacities from 5 to 80 kWh in 5 kWh increments. For each combination, the hourly dispatch model calculated annual backup energy, renewable fraction, and battery utilization. The feasible design with the minimum levelized cost of served energy was selected. A grid search was chosen because the two-variable design space was small and because it provides complete reproducibility. This approach can later be replaced by PSO or NSGA-II when additional components and control variables are introduced [11-13].

The net present cost included initial PV, battery, inverter, and controller investments; annual operation and maintenance; backup energy expenditure; and a discounted battery replacement in year 10. The discounted levelized cost was calculated as:

$$\mathrm{LCOE} = \frac{\mathrm{NPC}}{\sum_{y=1}^{N} \frac{E_{\text{load},y}}{(1+r)^y}} \tag{4}$$

where NPC is net present cost, N is the 20-year project life, and r is the real discount rate. Simple payback was calculated relative to a USD 0.30/kWh diesel or weak-grid benchmark and therefore excludes financing structure, tax effects, depreciation, and the monetary value of avoided production interruptions. All monetary values are in constant U.S. dollars.

Table 3
Technical and economic assumptions used for comparative screening

Parameter	Base value	Interpretation/source
Annual load	21,900 kWh	Representative 60 kWh/day productive MSME
Project life/discount rate	20 years / 8%	Sensitivity range: 6-10%
PV installed cost	USD 950/kWp	Sensitivity range: USD 750-1,150/kWp [31-33]
Battery installed cost	USD 320/kWh	Sensitivity range: USD 220-450/kWh [32-33]
Controller/inverter allowance	USD 1,000 + USD 80/kW	Screening allowance; replace with quotation
Annual O&M	1.5% PV; 1.0% battery/inverter	Real constant annual cost
Battery replacement	Year 10, 70% of the initial battery cost	Discounted replacement; simplified aging [6]
Battery usable fraction/round-trip efficiency	90% / 90%	Pre-feasibility operational parameters
Backup energy cost	USD 0.30/kWh	Diesel or weak-grid proxy
Reliability constraint	RF ≥ 90%	Annual backup fraction ≤ 10%

3.5 Solar-Aligned Productive-Load Scenario

To evaluate demand-side flexibility, 8 kWh/day of deferrable demand was shifted from 18:00-24:00 to 10:00-16:00, with no change in total daily energy. The shift represents pre-cooling, water pumping, drying, ice production, washing, charging, or batch processing that can be scheduled during the solar window. Critical refrigeration and continuous process loads were not shifted. The full-capacity search was repeated so that the design could respond to the new timing, rather than simply recalculating the operation using the original components.

3.6 Sensitivity and Comparative Analysis

One-at-a-time sensitivity analysis varied PV cost, battery cost, backup energy cost, and the discount rate while keeping the selected base capacities fixed. This isolates the effect of each economic assumption on the mean LCOE across six sites. The study also calculated descriptive correlations among GHI, GTI, temperature, elevation, diffuse share, and PV yield. With only six sites, these correlations are interpreted as descriptive indicators rather than inferential evidence of causality.

4. Results and Discussion

4.1 Solar Resource, Topography, and PV Yield

The annual resource comparison reveals a clear but relatively compact spread in East Java. Madiun recorded the highest GHI at 1957.2 kWh/m²/year, followed closely by Surabaya and Lamongan. Bangkalan had the lowest GHI at 1860.1 kWh/m²/year, while Malang had 1867.6 kWh/m²/year. The maximum-to-minimum spread was 5.2% for GHI and 5.4% for optimum-tilt GTI.

Although these differences appear modest, they are large enough to alter PV capacity at the boundary of a reliability constraint.

Annual specific PV yield ranged from 1430.8 kWh/kWp in Bangkalan to 1506.5 kWh/kWp in Madiun, a 5.3% spread. GHI and GTI were both almost perfectly correlated with modeled yield across the six sites (descriptive r = 0.997), confirming that the resource signal dominated the annual inter-city comparison. Temperature alone did not explain the ranking. Malang was the coolest site at 23.9°C but had lower irradiation and, consequently, a lower annual yield than the warmer, high-resource sites. This result is consistent with PV physics: lower temperature improves conversion efficiency, but cannot compensate for a sufficiently lower annual solar input [2-4].

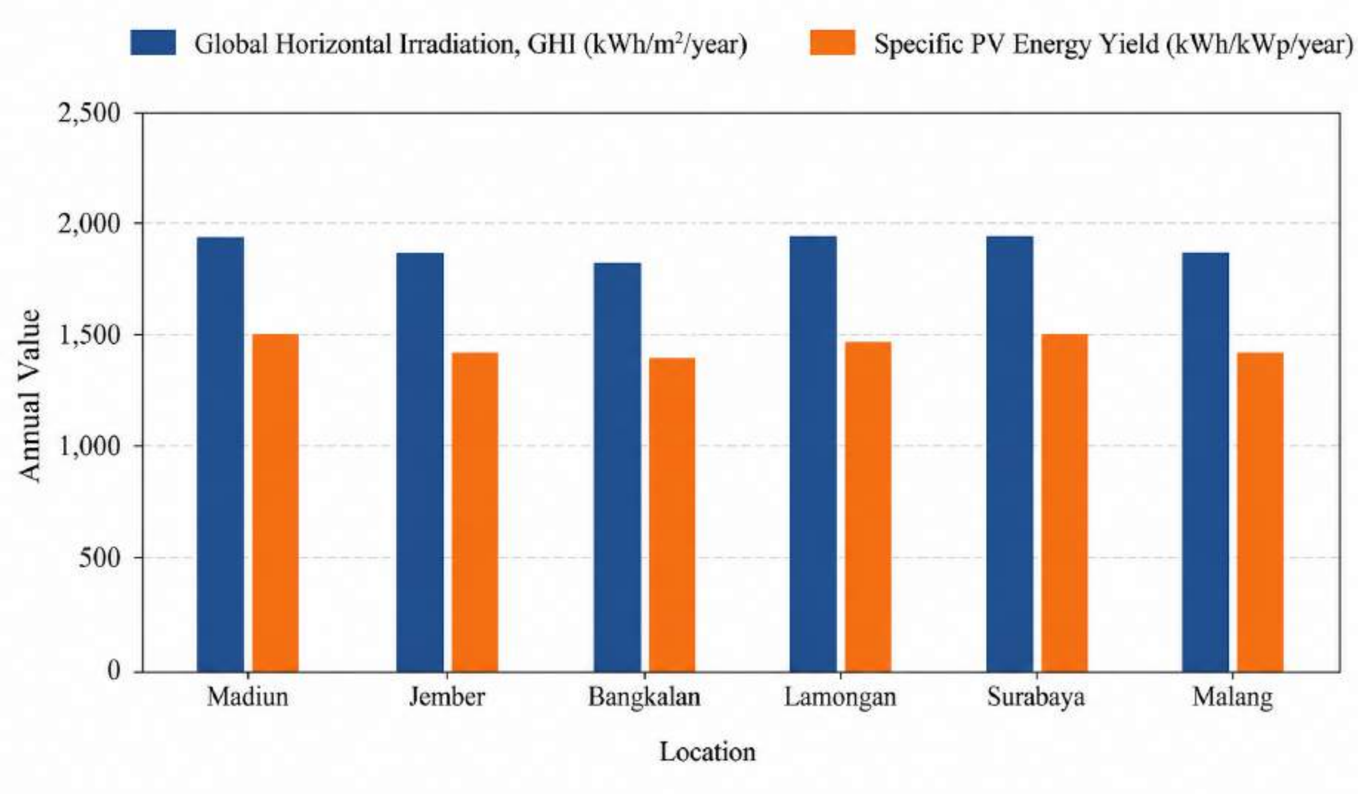

Fig. 3. Annual global horizontal irradiation and modeled specific PV yield across the six East Java sites

Table 4
Comparative modeled PV performance and seasonality metrics [37]

Site	12 kWp output (MWh/y)	Yield (kWh/kWp/y)	PR	Diffuse share (%)	Seasonal CV (%)	Min month	Min MWh	Max month	Max MWh
Madiun	18.078	1506.5	0.757	46.7	11.1	Feb	1.219	Sep	1.752
Jember	17.380	1448.3	0.759	44.3	10.6	Feb	1.216	Oct	1.678
Bangkalan	17.170	1430.8	0.758	48.0	11.6	Dec	1.215	Sep	1.693
Lamongan	18.011	1500.9	0.757	46.0	12.8	Feb	1.228	Aug	1.794
Surabaya	17.988	1499.0	0.754	44.6	15.1	Feb	1.208	Aug	1.861
Malang	17.315	1442.9	0.760	46.2	10.8	Feb	1.179	Aug	1.681

The modeled performance ratio was tightly grouped between 0.754 and 0.760 because the GSA reference configuration and loss assumptions were consistent. These values are somewhat lower than the average of approximately 0.81 reported by Kunaifi et al. [23] for polycrystalline systems in a tropical climate. Still, the figures are not directly equivalent because system age, inverter loading, availability, soiling, and calculation conventions differ. The comparison is useful mainly as a reminder that modeled and monitored PR should not be treated as interchangeable.

Bangkalan had the highest diffuse share at 48.0%, while Jember and Surabaya had lower shares of 44.3% and 44.6%. A high diffuse share can be advantageous under uniform cloud but generally corresponds to less direct radiation and can complicate short-term forecasting. The annual DNI ranking also differed from the GHI ranking: Surabaya had the highest DNI at 1479.0 kWh/m²/year, yet Madiun had slightly higher annual PV yield. This difference reinforces the value of using GTI and the full PV conversion model rather than selecting sites from DNI or GHI in isolation.

Elevation and temperature were strongly inversely related in this small sample (descriptive r = -0.894). Malang, at 451 m, was 3.7°C cooler than Bangkalan. Nevertheless, Malang's lower irradiation required nearly the same storage and had a higher LCOE than Madiun. For implementation, cooler highland conditions can improve module and battery thermal performance, but persistent cloud cover and lower annual resource availability still require sufficient PV area. Coastal lowlands have the opposite profile: high heat and corrosion risks may require ventilated mounting, corrosion-resistant hardware, and more frequent inspection, even where annual yields are strong.

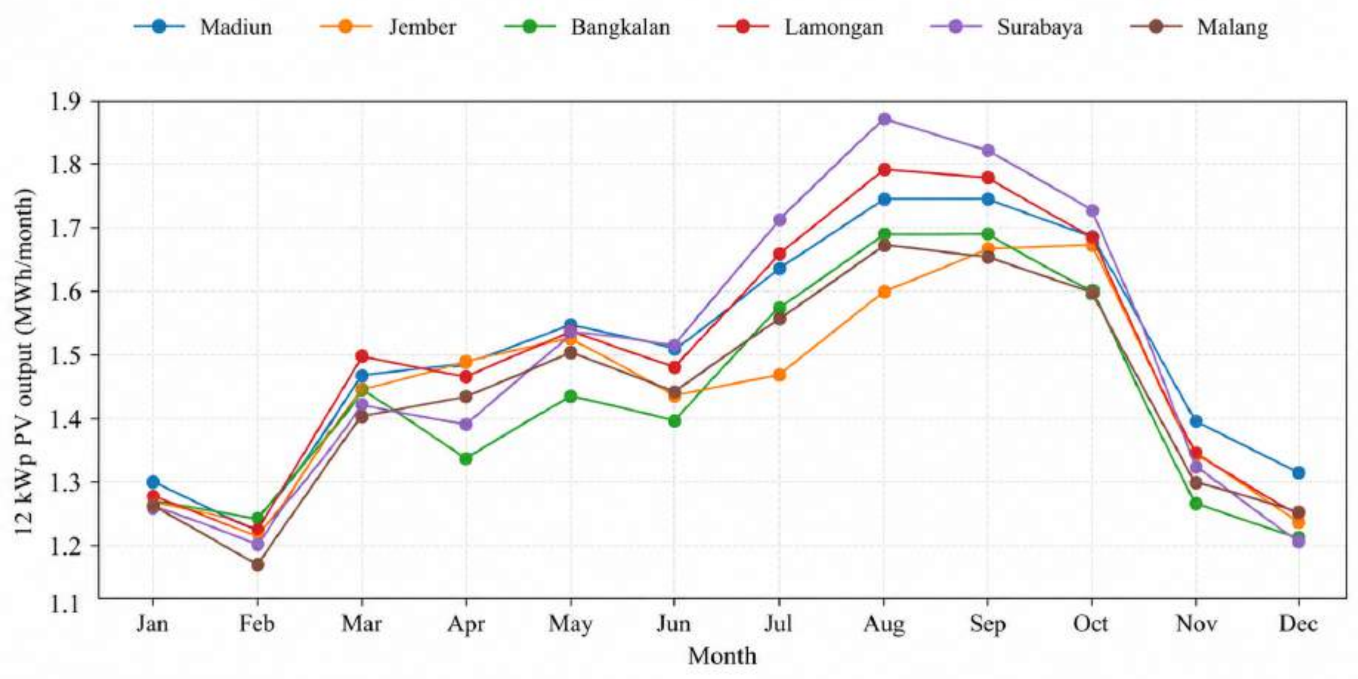

Fig. 4. Monthly production of the 12 kWp Global Solar Atlas reference system at each site

Monthly production shows a common pattern of weaker output early in the year, and stronger output from approximately July to October, but the magnitude differs. Surabaya had the highest seasonal coefficient of variation at 15.1%, rising from about 1.21 MWh in February to 1.86 MWh in August. Jember had the lowest coefficient at 10.6%. The annual totals, therefore, hide differences in seasonal reserve requirements. An enterprise with peak demand during the wet-season low-output months may need more backup energy or a larger operational reserve than a business with the same annual consumption but greater dry-season production.

The reconstructed profiles are smoother than real weather. Ramli et al. [8] measured abrupt output reductions during cloudy and rainy conditions in Surabaya, while Ihsan et al. [7] documented short-term spatial variability that cannot be reproduced by repeating a monthly average day. The present seasonality results should thus be interpreted as expected long-term behavior, not as evidence that 25 kWh of storage can cover every sequence of cloudy days.

4.2 Least-Cost PV-Battery Configurations

The least-cost feasible configurations used 16 kWp of PV and 25 kWh of battery at Madiun, Jember, Lamongan, Surabaya, and Malang. Bangkalan required 17 kWp because its lower specific yield caused the 16 kWp option to cross the reliability boundary. The result illustrates a threshold effect: a 5.3% annual-yield spread does not produce continuous changes in integer-sized equipment, but it can add one complete kWp when the design must satisfy RF ≥ 90%.

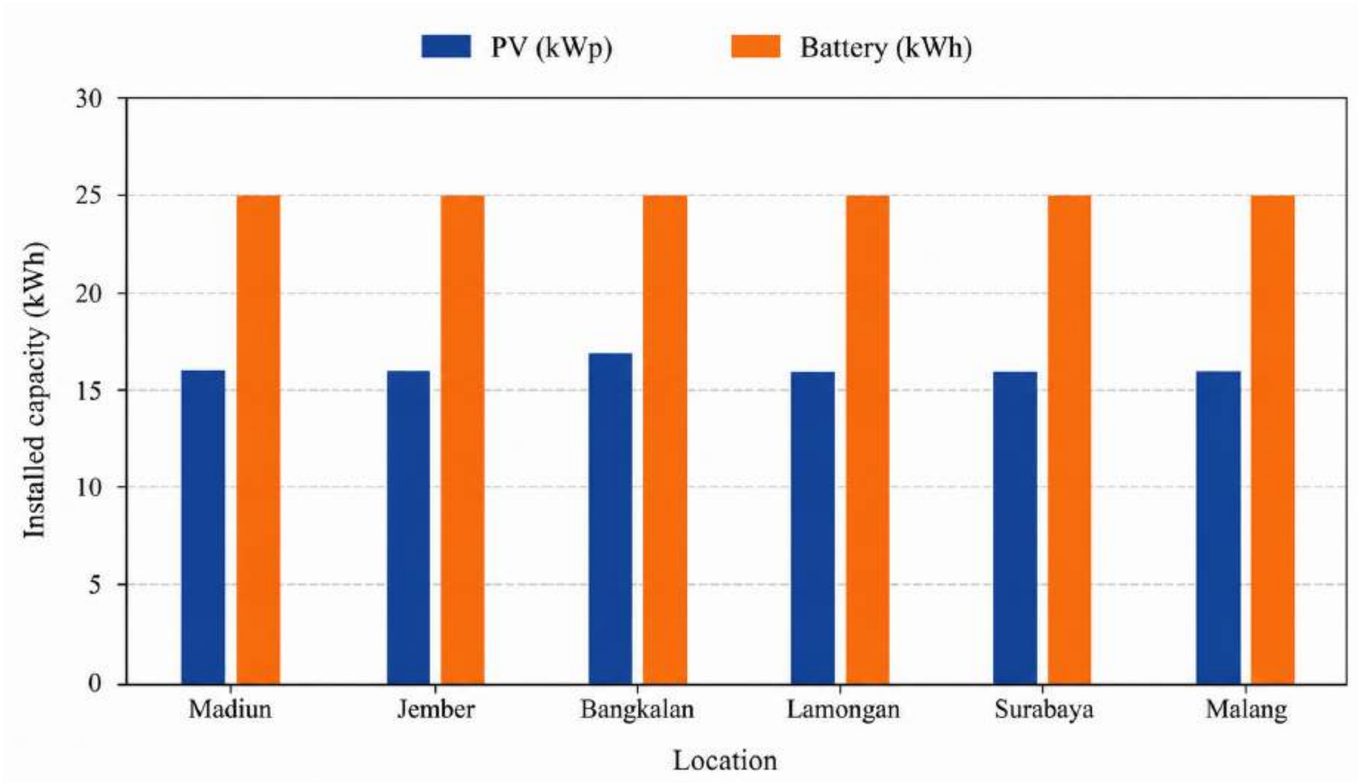

Fig. 5. Least-cost PV and battery capacities satisfying the renewable-fraction constraint

Table 5
Optimized technical and economic results for the original MSME load profile

Site	PV (kWp)	Battery (kWh)	RF (%)	Backup (kWh/y)	LCOE (USD/kWh)	Simple payback (y)	Critical autonomy at 2 kW (h)
Madiun	16	25	95.7	945	0.1586	4.28	11.2
Jember	16	25	94.1	1,296	0.1634	4.36	11.2
Bangkalan	17	25	96.6	743	0.1613	4.42	11.2
Lamongan	16	25	95.5	988	0.1592	4.29	11.2
Surabaya	16	25	95.0	1,093	0.1606	4.31	11.2
Malang	16	25	94.4	1,224	0.1624	4.34	11.2

Renewable fraction ranged from 94.1% in Jember to 96.6% in Bangkalan. Bangkalan's renewable fraction appears high despite its lower yield because the additional 1 kWp of PV moved its optimum farther above the minimum reliability boundary. Backup energy ranged from 743 to 1296 kWh/year, equivalent to approximately 2.0-3.6 kWh/day on an annual-average basis. This energy would not be used evenly: it would be concentrated in evening deficits and low-solar periods.

The common 25 kWh battery indicates that the representative load shape and minimum renewable fraction dominated the relatively narrow resource spread. With 90% usable energy and a 2 kW critical load, the battery provided about 11.2 hours of critical autonomy. Whole-enterprise autonomy would be much shorter at the 4.2 kW peak and depends on the state of charge when an outage begins. Therefore, the result should not be communicated as a guaranteed 11-hour business backup duration.

The LCOE ranged from USD 0.1586/kWh in Madiun to USD 0.1634/kWh in Jember. All values were below the USD 0.30/kWh diesel or weak-grid screening benchmark. Simple payback ranged from 4.28 to 4.42 years, with Bangkalan slightly longer due to its additional PV capacity. These values are comparable in scale to productive-use and cold-chain studies in Indonesia [18-19], but direct comparisons require caution because equipment prices, financing, subsidies, diesel logistics, and system boundaries differ.

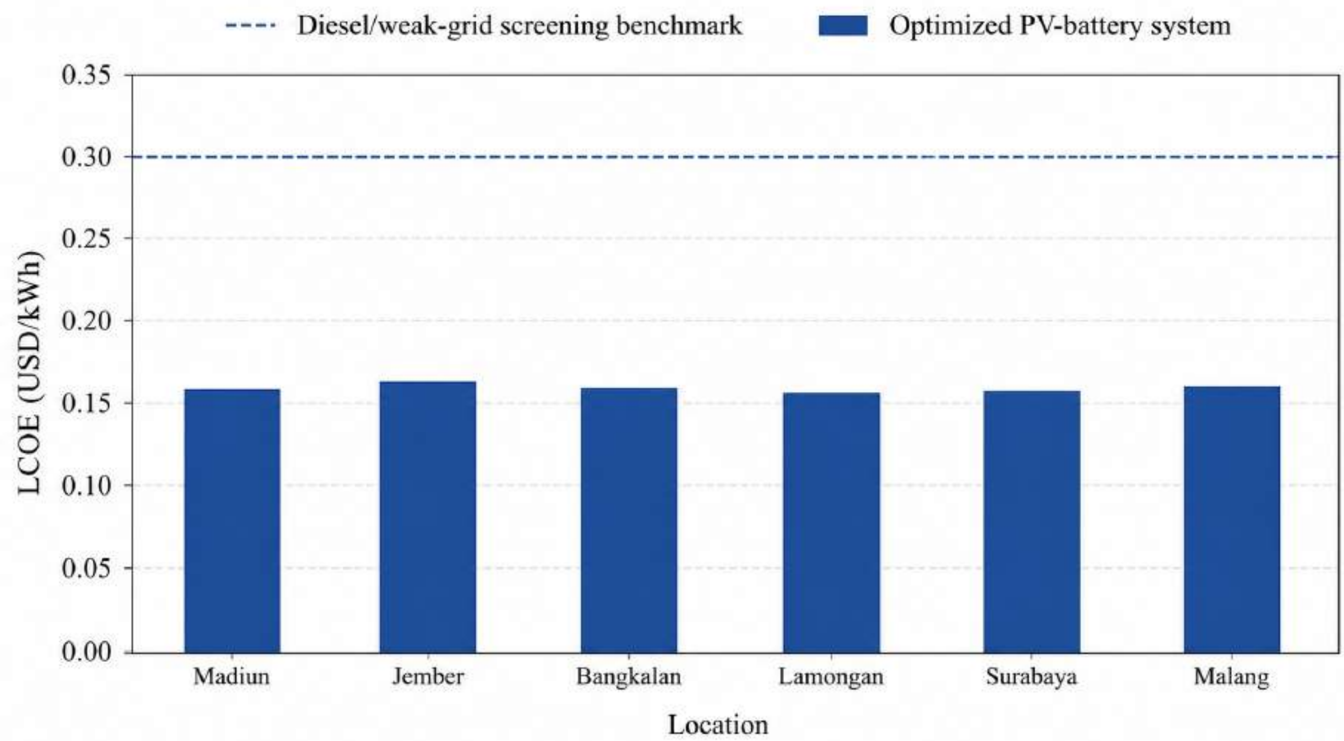

Fig. 6. Levelized cost of served energy compared with the diesel or weak-grid screening benchmark

The optimized capacities are consistent with the broader literature in two ways. First, Xu et al. [16] and Bawan et al. [17] found that local resource and demand assumptions materially affect the optimum, thereby supporting the 1 kWp difference observed here. Second, the optimization reviews by Ridha et al. [12] and Kumar et al. [14] emphasize that the choice of reliability metric affects the design. A stricter reliability requirement, a lower allowable depth of discharge, or a requirement for multi-day autonomy would increase the battery and possibly the PV array. The present result is therefore a cost-minimum under the stated RF criterion, not an absolute technical optimum.

4.3 Productive-Load Scheduling and Storage Reduction

Moving 8 kWh/day of flexible demand into the 10:00-16:00 solar window changed the optimum at every site. Battery capacity fell from 25 to 20 kWh, a 20% reduction, while PV capacity remained unchanged. The renewable fraction increased to 96.0-98.2% because a larger share of PV generation was consumed directly, and less energy passed through the battery. This is the central and counterintuitive result: shifting only 13.3% of daily energy changed storage at every site, whereas the 5.3% inter-city annual-yield spread changed the PV array by only 1 kWp and did not change battery capacity. Mechanistically, midday direct consumption bypasses charge-discharge losses and preserves battery energy for evening critical loads. The finding separates two control layers: local solar resource mainly sets the PV threshold, while load chronology mainly sets storage.

Table 6
Benefits of shifting flexible productive load into solar-generation hours

Site	Base battery (kWh)	Shifted battery (kWh)	Base LCOE	Shifted LCOE	LCOE reduction (%)	Shifted RF (%)	Shifted payback (y)
Madiun	25	20	0.1586	0.1421	10.4	97.7	3.91
Jember	25	20	0.1634	0.1470	10.0	96.0	3.99
Bangkalan	25	20	0.1613	0.1459	9.5	98.2	4.07
Lamongan	25	20	0.1592	0.1433	10.0	97.2	3.93
Surabaya	25	20	0.1606	0.1453	9.5	96.6	3.96
Malang	25	20	0.1624	0.1462	10.0	96.3	3.97

Fig. 7. Effect of solar-aligned productive-load scheduling on levelized cost

LCOE decreased by 9.5-10.4%, reaching USD 0.1421-0.1470/kWh. Simple payback improved to approximately 3.91-4.07 years. The benefit was consistent because the shifted energy was large enough to avoid one 5 kWh storage increment at all sites. In practice, the exact result would depend on how many hours the load can move, the permissible temperature or production range, and whether scheduling creates new demand peaks.

The result aligns with Shafira et al. [18], who showed that productive activities can improve hybrid-system utilization, and with the cold-chain assessment by Nugraha et al. [19]. It is also consistent with the broader MSME evidence synthesized by Rizkita and Prasetyo [20], which links decentralized renewable energy to enterprise performance while emphasizing contextual and financial constraints. The present study extends that literature by quantifying the storage implications of an identical scheduling intervention across six cities. For an MSME, the intervention may include pre-cooling a cold room, freezing thermal storage during midday, pumping water to an elevated tank, scheduling milling or drying batches, or charging equipment while PV output is high. These actions reduce battery capital cost and cycling burden, provided process and labor constraints are respected.

Load shifting should be designed with production staff rather than imposed as a purely electrical schedule. Critical loads must remain protected, food safety and quality requirements must be met, and labor arrangements may constrain daytime operations. A practical energy audit should therefore classify each load as critical, fixed, interruptible, or deferrable and assign an acceptable operating window before final system optimization.

4.4 Economic Sensitivity and Robustness

The base mean LCOE across the six sites was USD 0.1609/kWh. Battery cost and discount rate had the greatest influence among those tested, followed closely by PV cost. Increasing battery cost from USD 320 to USD 450/kWh raised the mean LCOE to USD 0.1824/kWh; reducing it to USD 220/kWh lowered the mean LCOE to USD 0.1444/kWh. A 10% discount rate raised the mean LCOE to USD 0.1787/kWh, while a 6% rate reduced it to USD 0.1441/kWh. These results demonstrate that financing terms can be as important as equipment price for capital-intensive MSME systems.

Table 7
One-at-a-time sensitivity of the mean six-site LCOE for the fixed optimized capacities

Parameter	Unit	Low input	Base input	High input	LCOE at low	LCOE at base	LCOE at high
PV installed cost	USD/kWp	750	950	1150	0.1437	0.1609	0.1782
Battery installed cost	USD/kWh	220.00	320.00	450.00	0.1444	0.1609	0.1824
Backup energy cost	USD/kWh	0.20	0.30	0.45	0.1562	0.1609	0.1681
Discount rate	%	6	8	10	0.1441	0.1609	0.1787

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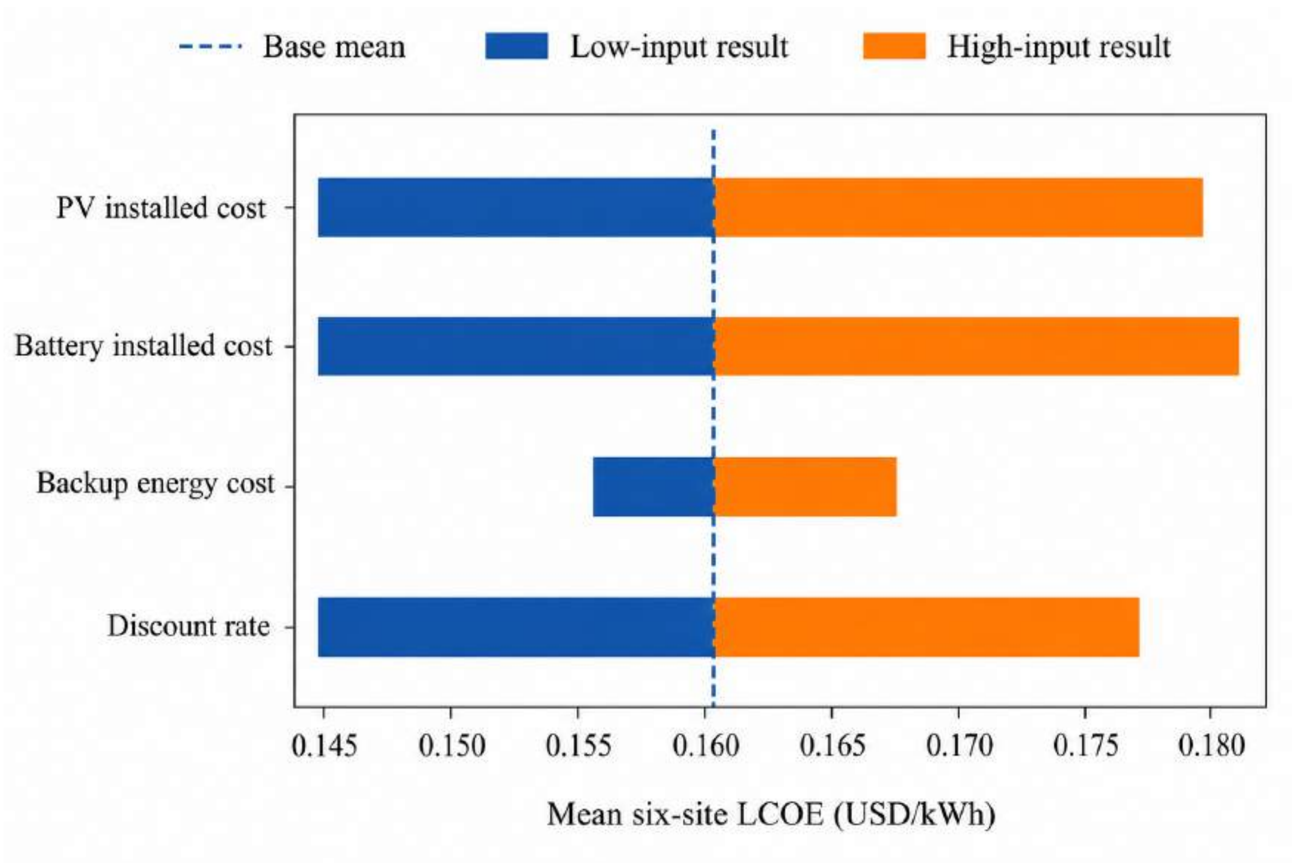

Fig. 8. One-at-a-time sensitivity of mean six-site LCOE around the base case

Backup-energy cost had a smaller influence in this particular model because the optimized systems already supplied more than 94% of annual demand from PV and batteries. Raising the backup cost from USD 0.30 to USD 0.45/kWh increased the mean LCOE to USD 0.1681/kWh. The effect would be larger for smaller renewable systems, more severe weather sequences, or enterprises with less daytime demand. The result should not be interpreted as evidence that the diesel price is unimportant; it reflects the high renewable fraction selected by the constraint.

The base configurations remained below the USD 0.30/kWh benchmark over all tested one-at-a-time ranges. However, this does not guarantee bankability because taxes, structural roof work, fire-protection systems, interconnection studies, financing fees, project-development costs, and downtime during maintenance were not included. The strongest robust design insight is therefore the load-shifting result: reducing battery capacity through operational alignment is less dependent on future battery-price forecasts and simultaneously reduces replacement exposure.

4.5 Location-Specific Engineering and Implementation Implications

Bangkalan is the clearest example of why a common provincial design can fail at a capacity boundary. Its low elevation and high temperature suggest thermal and corrosion precautions, while its lower yield required an additional kWp in the model. Surabaya has strong annual resources, but the highest seasonal variability, so urban shading surveys and load control are more important than the annual total alone would suggest. Malang demonstrates the opposite trade-off: cooler operation may improve component efficiency and life, yet the lower annual solar resource prevents battery or PV downsizing under the selected reliability target.

Table 8
Location-specific design implications

Site	Dominant observation	Pre-feasibility and engineering implications
Madiun	Highest modeled annual yield; moderate seasonality	Prioritize PV self-consumption; 16 kWp/25 kWh base design; verify agricultural dust and roof shading
Jember	Lower yield, mild temperature, lowest seasonal CV	Retain backup margin; validate wet-season refrigeration demand and local cloud persistence
Bangkalan	Hot coastal lowland; lowest yield; highest diffuse share	Add about 1 kWp in the base scenario; use ventilation, corrosion-resistant hardware, and conservative cleaning
Lamongan	High yield with stronger seasonal variation	Use seasonal SOC reserve and schedule agricultural processing during midday.
Surabaya	High yield and DNI, but the highest monthly variability; dense urban context	Assess urban shading, roof temperature, soiling, fire safety, and forecasting/load control.
Malang	Cool elevated site; lower irradiation	Use the temperature benefit but retain adequate PV area; examine highland cloud sequences and roof orientation.

Implementation should proceed through successive levels of evidence. First, a business should measure 15-minute demand, identify outage characteristics, and classify load flexibility. Second, the roof, electrical installation, shading, corrosion exposure, and fire-safety conditions should be surveyed. Third, an hourly optimization should be repeated using vendor-specific components and multiple weather years. Fourth, financing, applicable rooftop PV quotas, interconnection conditions, and permits should be screened in accordance with Ministerial Regulation No. 2/2024 [34]. Finally, commissioning data should be used to adapt battery reserve and productive-load schedules.

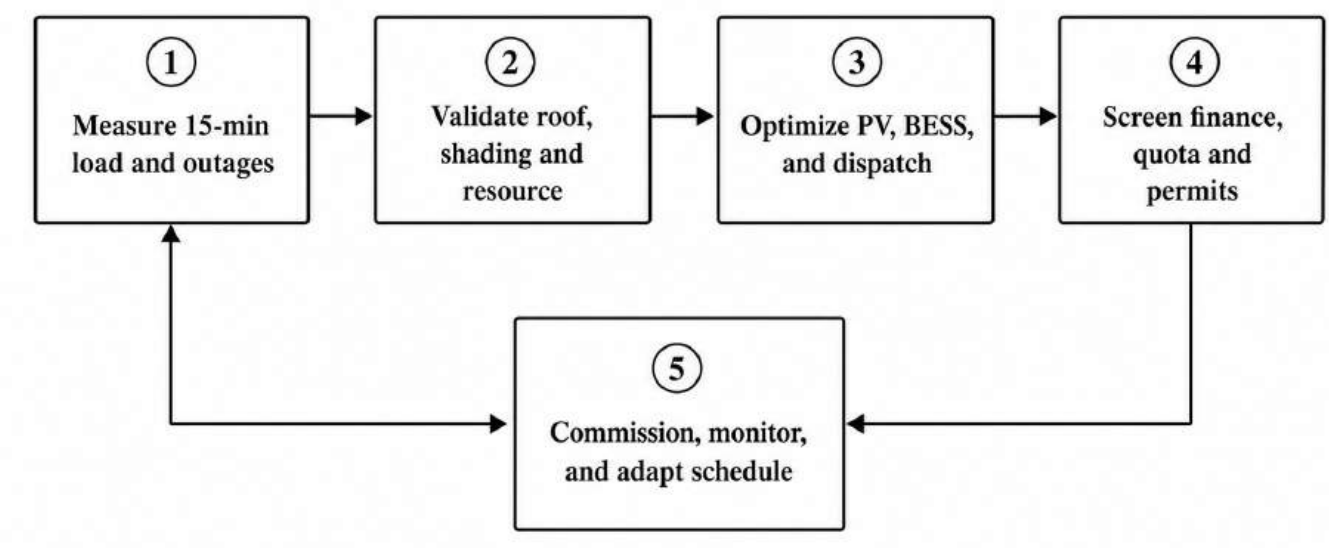

Fig. 9. Iterative implementation pathway from measured MSME demand to monitored operation

4.6 Comparison with the Literature and Study Contribution

The study generates a separation-of-effects insight rather than claiming that East Java requires six entirely different system architectures. Under a common load and reliability target, geographic resource differences mainly moved the discrete PV-capacity threshold, whereas operational flexibility moved storage. This is new and counterintuitive because conventional site screening often prioritizes annual irradiation. Yet, within the relatively narrow East Java resource spread, an operational change delivered a larger capacity and cost-effectiveness than moving among cities. The theoretical implication is that demand chronology should be treated as an endogenous design variable rather than a fixed boundary condition. For MSME programs, standardized equipment architecture may remain feasible, but the PV module count, battery reserve, mounting, maintenance, and load schedules should be configured based on local evidence.

Table 9
Comparative interpretation of the present findings against the literature

Theme	Findings from this study	Relationship to prior literature	Specific contribution
Local resource effect	Annual yield spread of 5.3%; Bangkalan requires 1 additional kWp	Ihsan et al. [7] and Xu et al. [16] support localized resource assessment	Converts regional variability into a discrete MSME capacity consequence
Tropical performance	Modeled PR of 0.754-0.760; strong caution on cloud/soiling	Kunaifi et al. [23] and Ramli et al. [8] report tropical PR and transient losses	Separates long-term modeled yield from short-term operational risk
Optimization	Transparent exhaustive search under RF ≥ 90%	Ridha et al. [12], Wali et al. [13], and Kumar et al. [14] support optimization methods	Provides an auditable two-variable baseline before advanced metaheuristics
Productive use	8 kWh/day load shift cuts battery by 20% and LCOE by 9.5-10.4%	Shafira et al. [18] and Nugraha et al. [19] report productive-use benefits	Quantifies identical scheduling intervention across six cities
Economic outcome	LCOE USD 0.159-0.163/kWh; payback 4.28-4.42 years	Indonesian hybrid studies show strong dependence on assumptions [16-18,26]	Uses one common cost framework to isolate location and timing
Future data	Monthly average-day reconstruction is adequate only for screening	Pfenninger and Staffell [29] and Gufron et al. [30] support high-resolution data	Defines a pathway to stochastic and adaptive MSME design
Design-lever hierarchy	Location mainly changes the PV threshold; load timing changes storage	Prior studies generally examine resource localization or productive use separately	Shows that shifting 13.3% of daily demand can have a larger sizing effect than a 5.3% inter-city yield spread

The study also clarifies the role of optimization sophistication. PSO and NSGA-II are valuable for high-dimensional or multi-objective design, but a transparent exhaustive search is sufficient to establish an auditable baseline with two capacity variables. In the present application, uncertainty in typical weather, the generic load, and screening costs is more consequential than the choice among competent search algorithms. The evidence hierarchy is therefore data first, algorithm second: advanced optimization adds value after site-specific inputs and additional objectives are available, not as a substitute for uncertain inputs.

5. Limitations

Three limitations directly bound the inference. First, the GSA values are modeled as long-term means, and the hourly PV profiles were reconstructed by repeating monthly average days. This deterministic representation smooths cloud ramps, multi-day low-irradiance sequences, interannual variability, local shading, orientation errors, and soiling. It can therefore understate battery depth-of-discharge excursions, the concentration of backup use, and the PV-storage margin needed for specific outage periods; the reported city ranking and annual energy balance should not be interpreted as guaranteed resilience.

Second, a single synthetic 60 kWh/day load profile was applied across all sites. This controlled the comparison but prevents inference to the diversity of refrigeration, milling, welding, retail, agricultural, and service MSMEs. In particular, the 20% storage reduction is conditional on 8 kWh/day being genuinely deferrable from 18:00-24:00 to 10:00-16:00 without creating a new peak or violating labor, food-safety, or process constraints. Enterprises with higher night loads or less flexibility may require larger storage; enterprises with stronger daytime coincidence may require less.

Third, the economic and reliability models are screening simplifications. A single discounted replacement represents battery aging; backup cost is a proxy; and taxes, financing fees, structural work, fire protection, tariffs, and avoided outage losses are excluded. The renewable fraction is an annual metric and does not guarantee service for the stated outage duration. The structured narrative review provides transparent thematic traceability but is not an exhaustive systematic review. Consequently, the results support comparative screening and hypothesis formation, not procurement or financing. The single next validation priority is a prospective field campaign that couples measured 15-minute MSME loads with site irradiance and outage chronology across contrasting East Java locations; stochastic optimization should follow those measurements rather than precede them.

6. Conclusion

The principal conclusion is not that one East Java city is universally superior, but that PV-battery design contains two separable levers. Across nearby locations, resource differences mainly determine whether the PV array crosses a discrete capacity threshold; load timing determines how much energy must pass through storage. The study's new and counterintuitive knowledge is that shifting 8 kWh/day (13.3% of demand) into solar hours reduced the selected battery by 20% at every site, a larger design effect than the geographic resource spread.

This yields practical decision rules for MSME owners and program designers. First, audit and classify loads before buying additional battery capacity: if approximately 8 kWh/day can be shifted to 10:00-16:00, test a 20 kWh option rather than a 25 kWh option while retaining the same PV capacity. Second, use the 16 kWp PV/25 kWh battery result only as a screening package for a 60 kWh/day enterprise; add PV capacity when local yield or reliability margins place the design near the threshold, as in Bangkalan. Third, interpret 11.2 h as autonomy for a 2-kW critical-load subset, not for the entire business.

The theoretical implication is that productive-load chronology should be optimized jointly with hardware because direct solar consumption can substitute for storage capital and cycling. The practical implication is “measure, shift, then size”: obtain interval load data, protect non-deferrable loads, reschedule feasible processes, and only then finalize PV and battery capacity using local weather and quotations. Under the present modeled-data limitations, these are defensible pre-feasibility rules rather than bankable specifications.

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Conflict of Interest Statement
The authors declare that there is no conflict of interest regarding the publication of this paper.

Author Contributions Statement
The contributions of the authors to this study are as follows: Marsya Aulia Rizkita led the conceptualization of the research, designed the methodology, conducted data analysis, and took the

primary responsibility for writing the manuscript. Singgih Dwi Prasetyo offered valuable insights into power plant engineering technology, contributing to the design of the methodology and assisting in interpreting results related to the technical aspects of photovoltaic-battery systems. Hadi Suwono played a significant role in shaping the study's design and methodology, particularly by incorporating biological and environmental factors and supporting data collection from the Global Solar Atlas. Nik Ahmad Nizam Nik Malek contributed to the development of the research framework, facilitated access to relevant data sources, and ensured the technical accuracy and clarity of the final manuscript during the review process. All authors collaborated in reviewing the final manuscript and approving it for publication, ensuring that their collective expertise was reflected throughout the study.

Data Availability Statement

The site-specific input data are included in the six Global Solar Atlas reports provided with the manuscript. The tables and figures presented can be reproduced using the equations, assumptions, monthly profiles, and capacity search ranges outlined in Section 3. Additionally, any calculation files should be stored in an institutional repository or made accessible by the corresponding author before publication.

Ethics Statement

This study used publicly available modeled solar-resource data and did not involve human participants, personal data, animals, or biological materials. Ethical approval and informed consent were therefore not applicable.

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