

Article

A Decision Support Framework for Solar PV System Selection in SMMEs Using a Multi-Objective Optimization by Ratio Analysis Technique

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Abstract

South African small, medium and micro enterprises, particularly township-based spaza shops, face barriers to adopting solar photovoltaic systems due to upfront costs, regulatory uncertainty, and limited technical capacity. This article presents a reproducible methodology for evaluating and selecting solar photovoltaic systems that jointly considers economic, technological, and legal/policy criteria for such enterprises. We apply multi-criteria decision making using the Multi-Objective Optimization by the Ratio Analysis method, integrating simulation-derived techno-economic metrics with a formal policy-alignment score that reflects registration requirements, tax incentives, and access to green finance. Ten representative system configurations are assessed across cost and benefit criteria using vector normalization and weighted aggregation to enable transparent, like-for-like comparison. The analysis indicates that configurations aligned with interconnection and incentive frameworks are preferred over non-compliant options, reflecting the practical influence of policy eligibility on investability and risk. The framework is lightweight and auditable, designed so that institutional actors can prepare shared inputs while installers, lenders, and shop owners apply the ranking to guide decisions. Although demonstrated in a South African context, the procedure generalizes by substituting local tariffs, irradiance, load profiles, and jurisdiction-specific rules, providing a portable decision aid for small enterprise energy transitions.

Keywords: solar photovoltaic system; small, medium and micro enterprises; decision support system; multi-criteria decision making; multi-objective optimization by ratio analysis; sustainability; technical evaluation; economic analysis; policy integration



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1. Introduction

When selecting the most suitable solar photovoltaic (PV) configuration from an ever-expanding array of viable alternatives each characterized by unique technical capabilities, cost structures, and levels of policy compliance Small, Medium, and Micro Enterprises (SMMEs) must possess a comprehensive understanding of their operational energy requirements alongside a precise knowledge of the evaluation criteria relevant to the design context [1–3]. Inadequate selection of system components or misalignment with contextual demands may result in excessive capital expenditure and reduced performance, potentially leading to premature system failure [4]. Such outcomes compromise not only the economic viability of the PV investment but also the long-term reliability and sustainability of energy supply for the enterprise. The selection of suitable system components

and configurations continues to be one of the most significant and complex tasks in the engineering design process, particularly when addressing diverse SMMEs application requirements, operational constraints, and performance objectives across varied deployment environments [5,6]. SMMEs must identify and select components with intended functionalities to ensure optimal system output, cost-effectiveness, and contextual suitability for the intended SMME application. This necessitates a careful balance between technical performance, lifecycle cost, and specific operational requirements. Selecting the optimal solar PV configuration amidst numerous, often conflicting, performance indicators constitutes a classic multi-criteria decision-making (MCDM) challenge. Thus, a systematic and analytically grounded approach to PV system selection becomes essential for SMMEs to identify the most suitable alternative for a given application and ensure technical efficiency, long-term economic viability, and policy compliance [7,8].

A growing body of research applies multi-criteria decision-making (MCDM) frameworks to advance sustainability in SMEs and renewable energy systems. Odoi-Yorke et al. [9] assessed seven hybrid renewable energy systems for SMEs in Ghana using six MCDM approaches and 25 criteria, consistently ranking PV/battery/diesel and PV/diesel/grid systems as the most resilient and cost-effective. Extending the focus on SMEs, Kumar et al. [10] developed a hybrid MARCOS–Entropy–CRITIC–MERECE model to prioritize rooftop solar adoption across ten Indian MSME sectors. Their results identified textiles and auto/engineering products as the most suitable sectors, thereby guiding targeted policy and investment strategies to accelerate green energy penetration. Parallel efforts address supplier selection and innovation adoption in SMEs. Musaad et al. [11] combined Fuzzy AHP and TOPSIS-Grey to evaluate green innovation ability in Saudi Arabian suppliers, finding that “Green Innovation Initiatives” dominate decision weights and that Supplier-3 represented the most sustainable option. Similarly, Wang et al. [12] integrated Fuzzy AHP with Green DEA for supplier evaluation in Vietnam’s SME food processing sector, identifying efficient decision-making units (DMUs) that aligned with environmental and operational criteria. Liaqait et al. [13] expanded this stream into supply chain decision-making, embedding fuzzy MCDM with multi-objective optimization to address sustainable supplier selection and order allocation in PV supply chains. Their results highlighted the salience of product cost, environmental management systems, and worker health and safety, while transportation and clearance costs strongly influenced allocation. Complementing these, Musaad et al. [14] examined institutional barriers to SME green innovation adoption, showing that political factors were most restrictive and recommending strategies such as strengthening research practices. Collectively, these studies underscore how hybrid fuzzy–MCDM approaches can support SMEs in navigating sustainability-oriented supplier networks, supply chains, and innovation challenges. In terms of spatial planning and siting of renewable energy, Belaid et al. [15] employed a GIS-based fuzzy AHP model to identify over 346,000 hectares of highly suitable land for PV deployment in Algeria’s remote agricultural regions, emphasizing agrivoltaics as a tool for rural electrification and sustainable farming. Agliata et al. [16] applied a Weighted Linear Combination approach to evaluate site suitability for Renewable Energy Communities in Italy’s Gargano district, finding that areas on the park’s periphery where infrastructure and demand converge with fewer restrictions were most suitable for REC development. Feng et al. [17] addressed rooftop solar deployment in China’s commercial sector, proposing a DEMATEL–ELECTRE III framework under a neutrosophic environment to mitigate information loss and compensation effects, ultimately ranking plan X1 as the most viable. Together, these studies highlight how MCDM models integrate technical, environmental, and socio-economic criteria to inform sustainable siting decisions across agricultural, regional, and commercial contexts. Research has also expanded toward PV system lifecycle

management. Abuzaid et al. [18] used an Analytic Network Process framework to evaluate cleaning strategies for PV modules in the MENA region, recommending partially automated cleaning as the most practical balance between efficiency and cost. At the end-of-life stage, Alzahmi and Ndiaye [19] applied an AHP-based framework to prioritize PV waste management strategies, finding recycling to be the most sustainable option, though stakeholder preferences varied. These contributions extend the MCDM literature by addressing not only adoption and siting but also operation and decommissioning, thereby covering the full lifecycle of PV sustainability challenges. These studies demonstrate the versatility of MCDM and hybrid fuzzy–optimization approaches in tackling sustainability challenges for SMEs and renewable energy systems. Whether focusing on system adoption, supply chain and supplier selection, spatial siting, or lifecycle management, these frameworks enable structured, evidence-based decisions that balance technical feasibility, economic performance, social priorities, and environmental sustainability. Prior solar-PV selection studies frequently deploy AHP/ANP, TOPSIS, MARCOS, ELECTRE and fuzzy hybrids, yielding valuable rankings but typically treating policy and legal constraints narratively rather than as scored, auditable criteria. Our framework differs in three respects. First, it formalizes policy eligibility (licensing/registration, incentive access, and green-finance readiness) as a bounded benefit criterion with a transparent rubric, so that legal and financing preconditions can compete directly with CAPEX, OPEX, LCOE, NPC, and reliability on the same decision surface. Second, it anchors inputs in simulation lineage (HOMER Grid) rather than expert ratings alone, improving unit consistency and auditability via vector normalization and documented weights. Third, it is portable: by substituting local tariffs, irradiance, load shapes, discount rates, and jurisdiction-specific interconnection and fiscal rules, the same procedure can be reproduced elsewhere without altering the method. Table 1 summarizes how this study compares with commonly used MCDM approaches in renewable-energy selection.

Although prior studies have employed a myriad of MCDM techniques to investigate technology and system configuration decisions, it is evident that the final ranking of alternatives remains highly sensitive to the assignment of criteria weights and the normalization method used to render the decision matrix dimensionless and comparable. This sensitivity necessitates careful methodological calibration to ensure that the evaluation process accurately reflects the diverse technical, economic, and policy considerations inherent in solar PV planning for SMMEs. It is also recognized that distinct normalization treatments are sometimes essential when handling a combination of beneficial and non-beneficial criteria within the decision matrix. This differentiation ensures that the evaluation process accurately preserves the intended directionality of performance maximizing beneficial outcomes while minimizing cost-related or adverse indicators. Moreover, certain MCDM techniques are mathematically intricate and computationally intensive rendering them less accessible to non-expert users or small-scale practitioners such as SMMEs. The implementation of such models often requires a deep understanding of linear algebra, optimization theory, or statistical computation, thereby introducing usability barriers and limiting practical adoption in resource-constrained decision environments. Consequently, decision-makers particularly within SMMEs require a method that is not only systematic and logically structured, but also intuitive and easy to implement without the need for advanced mathematical expertise. Such an approach should facilitate transparent comparisons across alternatives and offer reliable guidance even in environments constrained by technical capacity or computational resources.

Table 1. Comparison of common MCDM approaches with the present framework.

Ref.	Context/Scope	MCDM Method	Data Lineage	Policy/Legal Treatment	Main Finding	How this Paper Differs
[9]	SMEs in Ghana; hybrid RES options	AHP, ANP, TOPSIS, VIKOR, PROMETHEE, COPRAS	Expert + measured	Narrative only (not scored)	PV/battery/diesel & PV/diesel/grid ranked most resilient/cost-effective	We formalize policy as a scored benefit and link non-policy criteria to HOMER outputs, not only expert judgment.
[10]	Rooftop solar across 10 Indian MSME sectors	MARCOS–Entropy–CRITIC–MERECE (hybrid)	Secondary data	Narrative only	Textiles & auto/engineering prioritized	Targets system selection for a single enterprise type; policy score is auditable.
[11]	SME supplier selection (Saudi)	Fuzzy AHP + TOPSIS-Grey	Expert	Institutional factors discussed, not scored	“Green innovation initiatives” dominate	We do energy-system choice; policy eligibility competes with LCOE/CAPEX on same surface.
[12]	SME food processing (Vietnam)	Fuzzy AHP + Green DEA	Mixed	Not integrated as a criterion	Identifies efficient DMUs	Portable PV ranking pipeline with policy as a criterion + vector normalization.
[13]	PV supply-chain allocation	Fuzzy MCDM + multi-objective optimization	Model-based	Not integrated	Cost, EMS, H&S salient; logistics costs key	We focus on end-user system choice, not allocation.
[14]	SME green-innovation barriers	Fuzzy MCDM	Surveys	Political barriers highlighted, not scored	Policy barriers most restrictive	We quantify policy as eligibility/finance scores in the matrix.
[15]	Algeria PV siting	GIS + fuzzy AHP	GIS layers	Planning rules implicit	~346 k ha highly suitable	We address SME system configuration; theirs is siting.
[16]	Italy REC siting	Weighted Linear Combination	GIS/planning	Qualitative	Periphery zones best	Siting vs. SME system choice with policy scoring.
[17]	China commercial rooftop	DEMATEL–ELECTRE III (neutrosophic)	Expert	Implicit	Plan X1 ranked best	Lightweight, auditable method for non-experts; policy eligibility explicit.
[18]	PV O&M (cleaning)	ANP	Tech/field	—	Partially automated cleaning best	Different lifecycle stage; our novelty is policy-aware selection.
[19]	PV end-of-life	AHP	Stakeholder	—	Recycling preferred	Lifecycle end; our work is adoption with policy eligibility integrated.

In this study, the Multi-Objective Optimization based on Ratio Analysis (MOORA) method is proposed as a decision-making tool to rank solar PV system alternatives for a Spaza shop in Soweto, Gauteng. The model integrates technical and economic performance criteria for the Spaza shop's 11,300 total daily energy (Wh/day) ascertained through Hybrid Optimization of Multiple Energy Resources (HOMER GRID 1.11.4) simulations, alongside policy alignment scores that capture regulatory compliance, incentive eligibility, and SSEG readiness. MOORA effectively handles both beneficial and non-beneficial criteria by applying vector normalization along with weighted aggregation to ensure dimensional consistency across varied units. Due to its simplicity, transparency, and minimal mathematical burden, it proves particularly suitable for decentralized energy planning and guiding policy-aligned solar investment decisions in SMMEs like township Spaza shops. To the best knowledge of the authors, no prior study has applied the MOORA method in conjunction with HOMER GRID 1.11.4-derived metrics and policy scoring to optimize PV configurations specifically for SMMEs in the South African context. The latter highlights the novelty and contextual relevance of this research.

This paper addresses a methodological gap in small-enterprise solar planning: most multi-criteria studies either rely on expert judgments without simulation lineage or treat incentives and interconnection rules as narrative context rather than as ranked drivers. We ask whether a unified decision procedure that couples simulation-based techno-economics with an explicitly policy-aware multi-criteria aggregation can yield rankings that are both transparent and portable beyond a single jurisdiction. Our creative contribution is to (i) operationalize legal and financing eligibility as a scored benefit criterion inside the decision matrix, alongside cost and performance; (ii) link every criterion value to a reproducible data source (HOMER GRID 1.11.4 outputs or codified policy rules); and (iii) demonstrate a light-weight normalization and weighting scheme that preserves auditability for non-specialists. The empirical setting is a Soweto Spaza shop, but the method is designed for general use wherever local tariffs, irradiance, loads, and policy rules can be substituted. In this way, the study contributes scientifically by extending MCDM practice to include an auditable policy criterion and simulation-grounded metrics, and practically by delivering a transparent, easy-to-use framework that can guide investment and compliance decisions for SMMEs across varied contexts.

The remainder of the manuscript is organized as follows: Section 2 describes the materials and methods including the study site, technical and economic evaluation, policy integration, and the proposed multi-objective decision-making approach. Section 3 presents the results derived from the MOORA analysis and Section 4 concludes the study with key insights and future recommendations.

2. Materials and Methods

The methodological framework adopted in this study encompasses four main phases: data collection, simulation, optimization, and selection of the optimal design configuration. As illustrated in Figure 1, the process begins with gathering relevant technical, economic, and policy-based data inputs, followed by simulation using HOMER GRID 1.11.4 software to estimate system performance metrics.

These outputs are then structured into a decision matrix, normalized, and weighted before computing MOORA scores. The final output yields an optimal configuration that meets the multidimensional performance expectations of SMMEs operating in resource-constrained township economies.

We first assembled the inputs: (i) 8760-hour solar and meteorological series for the Soweto coordinates from profileSOLAR [20]; (ii) the shop load profile derived from appliance ratings and use durations and expanded to an hourly curve; (iii) tariff schedules as

modeled in HOMER GRID 1.11.4; and (iv) policy parameters (licensing thresholds, SSEG registration, and fiscal incentives) summarized in Section 2.4 for later scoring. Using these, HOMER GRID 1.11.4 ran a 25-year analysis with a nominal discount rate of 8% and inflation of 2%, applying PV derating consistent with local irradiance, converter efficiency of ~95%, and manufacturer-typical lifetimes for batteries and power electronics. The software produced the techno-economic outputs used as criteria NPC, LCOE, CAPEX/OPEX, reliability metrics, and component replacements. We then defined ten realistic design alternatives (A1–A10) that span common SMME options (grid-tied, hybrid/export-ready, and off-grid) by varying PV capacity, battery count, and converter sizing under identical load, weather, and financial assumptions. Finally, we applied MOORA for optimization/ranking: raw values were vector-normalized, criterion weights were, and composite scores y_i were computed by adding benefit criteria (reliability, policy alignment) and subtracting cost criteria (CAPEX, OPEX, LCOE, NPC). Consistency checks (dominance, monotonicity, and one-way weight perturbations) confirmed that the ranking behavior aligns with decision-theoretic expectations. The same workflow is portable beyond Soweto by substituting local tariffs, irradiance/load series, discount rates, and jurisdiction-specific interconnection and fiscal rules while retaining the identical MOORA pipeline.



Figure 1. Methodological Framework for Solar PV System Selection using MOORA.

2.1. Study Site

The study site for the investigation is a Spaza shop located in Soweto, Gauteng, located in the southern subtropics of Johannesburg, South Africa (Latitude: -26.2694 , Longitude: 27.8679). The site presents a favorable environment for solar PV energy generation given that it benefits from high solar irradiance throughout the year, making it a favorable position for both residential and commercial solar energy systems. The PV generation potential oscillates seasonally with spring producing the highest energy output and winter the lowest. Utilizing 8760 hourly intervals of solar and meteorological data retrieved from the profileSOLAR [20] for the exact coordinates, the average daily energy yield per installed kilowatt-peak (kWp) of PV was computed for each season. This seasonal solar productivity is quantified using the Photovoltaic Generation Factor (PGF) which is an

essential metric representing the average daily solar energy output per unit of installed PV capacity. The values presented in Table 2 reflect the solar energy available to a 1 kWp PV system, averaged for each season.

Table 2. Soweto seasonal PV performance.

Season	Daily Solar Output (kWh/kWp/Day)
Summer	6.42
Autumn	5.77
Winter	4.74
Spring	7.23

The Monthly average solar global horizontal irradiance (GHI) data for Soweto, South Africa, is illustrated in Figure 2.

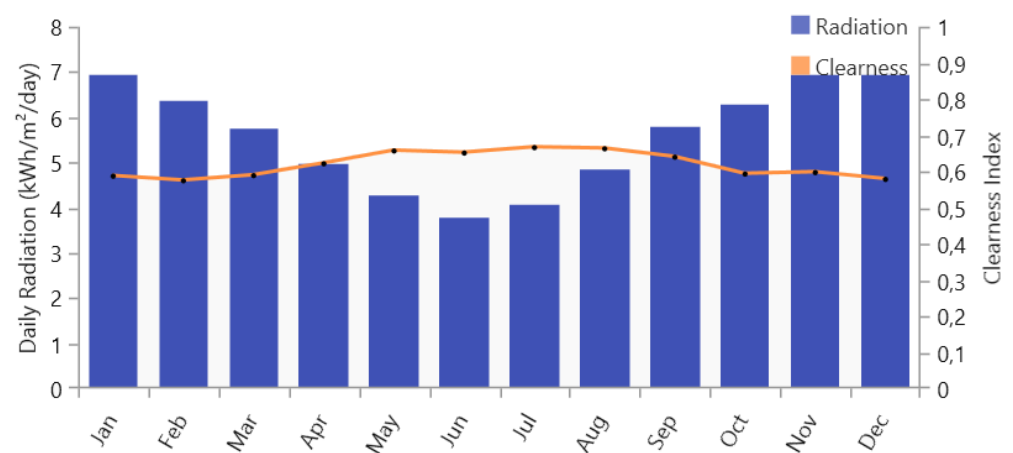


Figure 2. Monthly Average Solar Global Horizontal Irradiance (GHI) Data—Soweto, South Africa [21].

To maximize solar output in Soweto, a fixed tilt angle of 25° North is recommended for PV panel installation [20]. This accounts for the region's latitude and the solar elevation variation throughout the year. For systems with adjustable tilt, Table 3 presents the recommended seasonal angles for enhanced efficiency.

Table 3. Soweto recommended PV panel installation tilt angles.

Season	Optimal Tilt Angle
Summer	10° North
Autumn	32° North
Winter	42° North
Spring	20° North

Although the climate in Soweto is conducive to solar PV performance, local environmental conditions such as dust accumulation and summer thunderstorms may temporarily impact panel efficiency or system integrity. These challenges can be mitigated by:

- Implementing regular cleaning protocols.
- Installing surge protection and grounding equipment.

Given Soweto's high daily solar output and its manageable environmental factors, this location offers strong potential for sustainable solar development. The availability of reliable solar data and optimized panel orientation allows for informed planning and cost-effective deployment of solar PV systems.

2.2. Technical Evaluation

2.2.1. Load Profile Calculations for Spaza Shop

The electrical load demand under consideration for the Spaza shop with rated power consumption of appliances in watts (W) along with their daily operating time is tabulated in Table 4.

Table 4. Load profile of the Spaza shop.

Appliance	Rating (W)	Qty	Total (W)	Duration (h/Day)	* TDE (Wh/Day)
Display fridge/chest freezer	500	1	500	12	6000
Stand-alone fridge	200	1	200	7.2	1440
Electric kettle	1500	1	1500	1	1500
Microwave	800	1	800	0.5	400
LED lighting	15	4	60	12	720
Point of Sale (POS) device	10	1	10	12	120
Smartphone charging & router	10	2	20	12	240
Fan/small cooling unit	30	1	30	8	240
Weighing scale/till system	50	1	50	8	400
TOTAL			3170		11,300

* TDE—Total Daily Energy.

The Total Daily Energy demand was evaluated as expressed in Equation (1).

$$Total\ Daily\ Energy = \sum_{i=1}^N (Power_i \times Hours_i) \quad (1)$$

where

N —The number of appliances considered in the load analysis;

i —An index representing each individual appliance (from 1 to N);

$Power_i$ —The rated power of the i -th appliance, in watts (W);

$Hours_i$ —The number of hours per day the i -th appliance is used.

The electrical load demand data was consequently inserted into HOMER GRID 1.11.4 for evaluating the average load as expressed in Equation (2). The average load is the total daily energy consumption divided by the number of hours in a day. It is crucial for sizing the solar PV and battery system to ensure continuous and efficient power supply for the spaza shop's daily operations.

$$Average\ Load = \frac{Total\ Daily\ Energy}{24\ Hours} \quad (2)$$

$$\therefore Average\ Load = \frac{11300}{24\ Hours} = 470.83\ W$$

The load factor which indicates how efficiently electrical power is used in the Spaza shop over a period was evaluated as expressed in Equation (3). It compares the average load to the peak (maximum) load when assuming possible simultaneity of appliances. Higher values closer to 1 mean steady usage while lower values indicate peaky or inefficient consumption.

$$Load\ Factor = \frac{Average\ Load}{Peak\ Load} \quad (3)$$

$$Load\ Factor = \frac{470.83}{3170} = 0.1485$$

The load factor of approximately 0.1485 which implies the Spaza shop is using 14.85% of its maximum load capacity on average. Figure 3 demonstrates the synthesized load profile for the Spaza shop based on observed appliance usage patterns. The yearly profile (Figure 3a) illustrates hourly demand variation across the entire year with load concentrated between 08:00 and 16:00 reflecting typical business hours. The daily profile (Figure 3b) shows that energy demand peaks during mid-morning and early afternoon, consistent with refrigeration and lighting use. The seasonal profile (Figure 3c) indicates relatively stable load characteristics throughout the year, with slight increases during summer months due to additional cooling requirements.

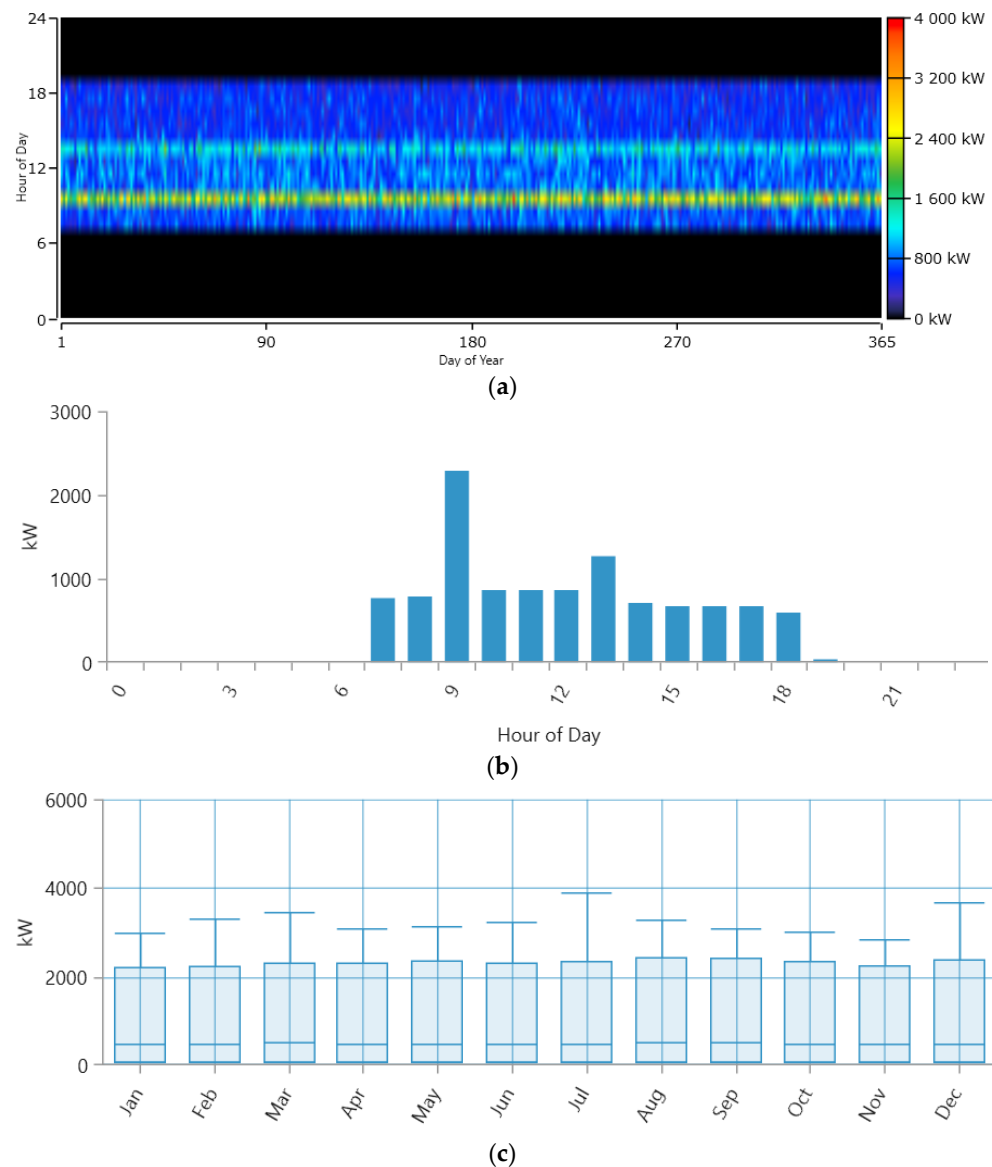


Figure 3. Load profile of the Spaza shop. (a) Yearly. (b) Daily. (c) Seasonal.

2.2.2. Photovoltaic System Design for Spaza Shop

The PV system of the Spaza shop is sized using a 30% margin to account for inverter losses, wiring inefficiencies, and battery round-trip losses using Equation (4) to Equation (12).

$$Total\ Daily\ Energy_{Adjusted} = Total\ Daily\ Energy \times 1.3 \quad (4)$$

$$\therefore Total\ Daily\ Energy_{Adjusted} = 11300 \times 1.3 = 14690\ Wh/day$$

It follows that the size of the required solar panel can be evaluated as expressed in Equation (5).

$$PV_{System_size} = \frac{Total\ Daily\ Energy_{Adjusted}}{Panel\ Generation\ Factor\ (PGF)} \quad (5)$$

PGF is the average number of peak sun hours per day at the installation site in Soweto which converts rated PV capacity (W_p) into expected daily energy output factoring in local solar irradiance and system performance. The seasonal solar productivity is quantified using PGF expressed in kWh/kWp/day. The PGF is computed as the unweighted average of seasonal irradiation values ascertained from Table 2, i.e., G_{Season} as expressed in Equation (6).

$$PGF = \frac{G_{Summer} + G_{Autumn} + G_{Winter} + G_{Spring}}{4} \quad (6)$$

$$\therefore PGF = \frac{6.42 + 5.77 + 4.74 + 7.23}{4} = 6.04 \text{ kWh/kWp/day}$$

$$\therefore PV_{System_size} = \frac{14690}{6.04} = 2.43 \text{ kW}_{peak}$$

The number of solar panels required to meet the desired system size PV_{System_size} can be evaluated as expressed in Equation (7).

$$PV_{Panel\#} = \frac{PV_{System_size}}{P_{R-PV}} \quad (7)$$

where

$PV_{Panel\#}$ —Number of Solar Panels to meet the desired PV_{System_size} ;
 P_{R-PV} —Rated power of the PV panel.

In practical solar PV system design, the rated output of photovoltaic modules typically determined under Standard Test Conditions (STC) does not always reflect actual performance in real environmental settings. Two critical adjustments are necessary to model the real output power of a PV module accurately: for irradiance variation and another for cell temperature effects. These are captured by Equations (8) and (9). The temperature of PV cells is typically higher than the surrounding ambient air temperature due to absorbed sunlight. Equation (8) can be employed to estimate this temperature rise under field conditions.

$$T_c = T_{amb} + (0.0256 \times G) \quad (8)$$

where

T_c —Cell temperature ($^{\circ}\text{C}$);
 T_{amb} —Ambient air temperature in $^{\circ}\text{C}$;
 G —year-round average PV output in Soweto (W/m^2).

$$\therefore T_c = 30 + (0.0256 \times 850) = 30 + 21.76 = 51.76 \text{ }^{\circ}\text{C}$$

This model provides a simplified yet effective means of determining cell temperature under varying irradiance levels, which directly impacts the PV system's voltage and power output. To account for the combined effects of solar irradiance and temperature variation

on photovoltaic module output, the corrected output power P_{PV} is calculated as follows in Equation (9).

$$P_{PV} = P_{R-PV} \times \left(\frac{G}{G_{ref}} \right) \times [1 + K_T(T_c - T_{ref})] \quad (9)$$

where

P_{R-PV} —Rated power of the PV panel;

G_{ref} —Standard irradiance (1000 W/m²);

K_T —Temperature coefficient (-3.7×10^{-3} per °C);

T_{ref} —Reference temperature (25 °C).

$$\therefore P_{PV} = P_{R-PV} \times 0.7654 \quad (10)$$

Equation (10) enables the correction of PV output by scaling the rated power according to actual irradiance and then adjusting for the thermal degradation or enhancement of performance due to cell temperature. This means the real-world output is 76.54% of the rated power under Soweto's average operating conditions. The number of panels needed for the spaza shop based on real-world Soweto conditions using the derated output in Equation (10) are computed using Equation (7) and tabulated in Table 5.

Table 5. Comparison of theoretical and actual panel requirements for a 2.43 kW_{peak} solar PV system in Soweto.

Panel Type	Rated Power	Panels Required (Theoretical)	Real Output (@76.5%)	Panels Required (Actual)
100 W Panel	100 W	25	76.5 W	32
400 W Panel	400 W	7	306 W	8
700 W Panel	700 W	4	535.5 W	5

The results highlight how panel selection directly affects both the physical footprint and the economic efficiency of a solar PV system. There is a critical need to factor in system derating when sizing for real-world performance especially in locations like Soweto with strong but variable irradiance levels.

2.2.3. Battery Storage System Sizing for the Spaza Shop

The battery storage component is essential for ensuring power continuity during periods of low solar generation or grid outages particularly for critical loads such as refrigeration, lighting, and POS systems in the Spaza shop. Battery sizing is based on the adjusted daily load and the desired level of autonomy, i.e., the number of days the system should continue to supply energy without solar input. The battery capacity required can be evaluated as expressed in Equation (11).

$$\text{Battery Capacity} = \frac{\text{Total Daily Energy}_{\text{Adjusted}} \times \text{Autonomy}(\text{days})}{\text{Depth of Discharge (DoD)}} \quad (11)$$

DoD is the usable portion of battery capacity is typically ~0.5 for lead-acid and ~0.8–0.9 for lithium-ion batteries. A lithium-ion battery chemistry was selected due to its high cycle efficiency, deeper depth of discharge, and longer lifespan compared to traditional lead-acid options. A DoD of 80% is applied which aligns with typical manufacturer-recommended limits for Li-ion systems and ensuring optimal performance without compromising battery

health. Assuming a 2-day autonomy and a DoD of 0.8 for a lithium-ion battery, then the battery capacity is:

$$\therefore \text{Battery Capacity} = \frac{14690 \times 2}{0.8} = 36725 \text{ Wh} = 36.73 \text{ kWh}$$

This value represents the total energy storage capacity required. If 48 V battery modules are selected, then be selected the battery bank capacity, i.e., the total amount of electric charge that a battery bank can deliver over time, measured in ampere-hours (Ah) can be expressed as follows in Equation (12).

$$\text{Battery Bank Capacity} = \frac{\text{Battery Capacity (Wh)}}{V_{\text{System}}} \quad (12)$$

where

V_{System} —Nominal voltage of the battery bank.

$$\therefore \text{Battery Bank Capacity} = \frac{36725}{48} = 765.1 \text{ Ah}$$

This means your 48 V battery bank needs to provide 765.1 Ah of capacity to meet your shop's energy demands with autonomy and derating considered. Then the required number of batteries for this system can be expressed as follows in Equation (13).

$$\text{Number of Batteries} = \frac{\text{Battery Bank Capacity (Ah)}}{\text{Capacity of One Battery (Ah)}} \quad (13)$$

$$\therefore \text{Number of Batteries} = \frac{765.1}{200} \approx 3.83 \Rightarrow 4 \text{ battery modules}$$

A total of $4 \times 48 \text{ V } 200 \text{ Ah}$ batteries is then required to provide 38.4 kWh of storage, ensuring 2-day autonomy with an 80% depth of discharge.

2.2.4. Inverter and Charge Controller Sizing

The inverter is responsible for converting the DC power from the PV system and batteries into usable AC power for shop appliances. Its size must be sufficient to handle the peak power demand and surge loads from startup currents. The minimum inverter capacity, P_{inv} , is calculated based on the peak load with an added design safety margin as follows in Equation (14).

$$P_{inv} = \text{Peak Load} \times \text{Inverter Margin} \quad (14)$$

Assuming a 25% margin, then P_{inv} is:

$$P_{inv} = 3.17 \text{ kW} \times 1.25 = 3.96 \text{ kW}$$

Thus, a 4 kW pure sine wave inverter is suitable for the Spaza shop to reliably handle startup surges from the kettle and microwave. Since the battery bank operates at 48 V DC, the inverter should match this system voltage for compatibility and efficiency. The charge controller regulates current and voltage from the PV panels to the battery bank, preventing overcharging. For Maximum Power Point Tracking (MPPT) controllers, the sizing involves both voltage and current parameters. This controller voltage rating should match the battery bank voltage, i.e., 48 V DC. The controller current rating is evaluated as shown in Equation (15).

$$I_{cc} = \frac{PV_{System_size}}{V_{System}} \times 1.25 \quad (15)$$

Therefore, a 60–80 A MPPT charge controller rated for 48 V is required to safely manage PV input under full sun conditions.

2.3. Economic Analysis

Based on the PV sizing results of 2.43 kW_{peak} and battery storage requirement of 36.7 kWh (Section 2.2), HOMER GRID 1.11.4 simulations were configured to reflect these system capacities with associated CAPEX, O&M, and replacement cost inputs, as shown in Figures 4 and 5. Economic analysis was conducted in HOMER GRID 1.11.4 software using a nominal discount rate of 8% and an inflation rate of 2% over a 25-year project lifetime. Cash flows and NPC values reported are based on this inflation-adjusted lifecycle planning model. Figure 4 summarizes the cost structure input interface used in HOMER GRID 1.11.4, including derating factors and optimizer settings tailored to reflect site-specific conditions in Soweto.

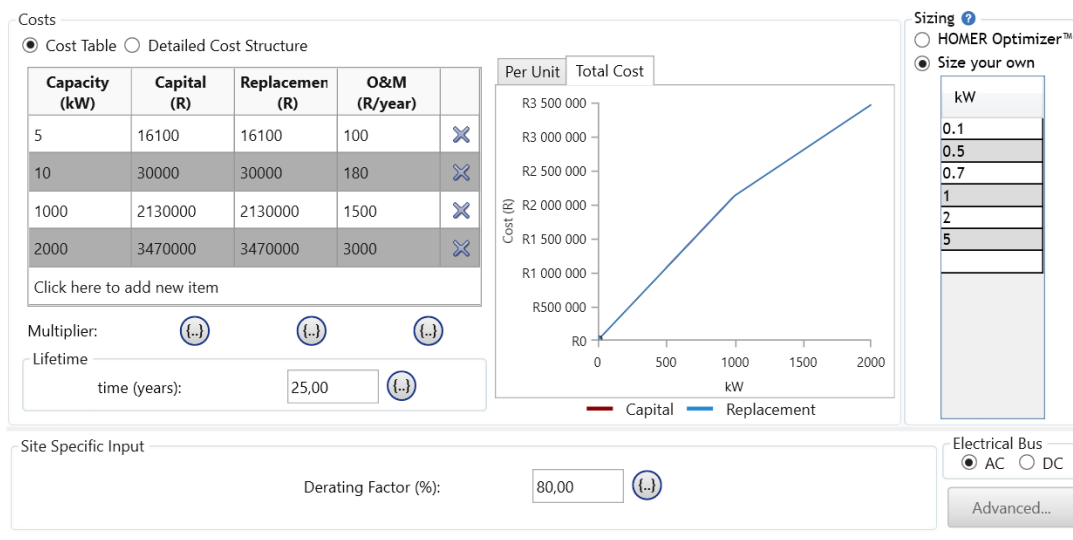


Figure 4. HOMER GRID 1.11.4 interface showing cost input structure and optimization settings for the solar PV system economic analysis.

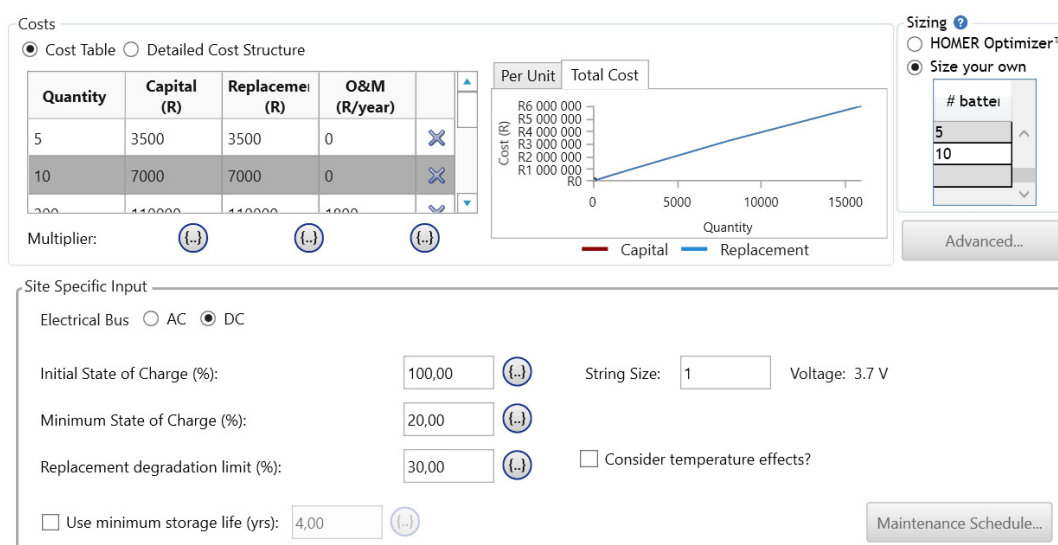


Figure 5. Battery Energy Storage System (BESS) Economic Inputs in HOMER GRID 1.11.4.

HOMER GRID 1.11.4's built-in optimizer was enabled to simulate multiple sizing scenarios, minimizing total lifecycle cost while meeting daily energy demand and reliability constraints. Similarly, Figure 5 illustrates the battery economic parameters, including minimum state-of-charge thresholds, degradation limits, and replacement triggers.

For the inverter/rectifier system, a capital cost of R4600 was assigned to a 1 kW converter and R9000 for a 2 kW unit. Replacement costs were kept equal to capital costs, while annual O&M costs were assumed to be zero, consistent with typical converter lifespan and minimal maintenance requirements. Both the inverter and rectifier units were configured with an efficiency of 95%, and a lifetime of 15 years was assumed. The relative capacity for AC-DC and DC-AC conversion was set at 100% to ensure full power handling capability. The converter simulation details in HOMER GRID 1.11.4. is illustrated in Figure 6.

Costs

Capacity (kW)	Capital (R)	Replacement (R)	O&M (R/year)
1	R4 600,00	R4 600,00	R0,0
2	R9 000,00	R9 000,00	R0,0
0	R0,0	R0,0	R0,0

Click here to add new item

Multiplier: [.] [.] [.]

Sizing

☐ HOMER Optimizer™

☒ Size your own

kW

0

1

2

3

4

5

Inverter Input

Lifetime (years): 15,00 [.]

Efficiency (%): 95,00 [.]

Rectifier Input

Relative Capacity (%): 100,00 [.]

Efficiency (%): 95,00 [.]

Figure 6. Converter Simulation Details in HOMER GRID 1.11.4.

All techno-economic outputs (tables and figures reporting costs, net present cost, levelized cost of energy, reliability, converter/battery metrics, monthly production, and emissions) were generated in HOMER Grid 1.11.4. Solar and meteorological time series (8760 hourly values for the study coordinates) were obtained from profileSOLAR [20]. Load-profile syntheses and MOORA computations were processed in Microsoft Excel 16.66.1; plots that reproduce model interfaces are HOMER GRID 1.11.4 exports/screenshots annotated by the authors. Unless otherwise stated, monetary values are in ZAR (nominal); the multi-criteria evaluation uses deterministic MOORA (vector normalization and weighted aggregation) without inferential statistics.

2.4. Policy Integration

The adoption of solar PV technologies by South African SMMEs particularly in township economies is increasingly shaped by a multi-tiered policy ecosystem. National energy regulations, fiscal incentives, provincial strategies, and local Small-Scale Embedded Generation (SSEG) programs now form a synergistic policy architecture aimed at lowering entry barriers, improving compliance, and accelerating adoption. Embedding these frameworks into the decision-making process ensures that the PV system alternatives evaluated through the MOORA method are not only technically viable and economically sound but also policy-aligned a crucial dimension for small businesses seeking funding, licensing, or grid connection.

2.4.1. NERSA Licensing Exemptions (≤ 100 kW Rule)

The National Energy Regulator of South Africa (NERSA), through the 2021 Amended Schedule 2 of the Electricity Regulation Act (ERA) introduced critical reforms to enable licensing exemptions for Small-Scale Embedded Generation (SSEG) systems with a capacity of up to 100 kW intended primarily for self-consumption [22–24]. According to this regulation, qualifying systems do not require a generation license but must be registered with the local distribution authority, such as City Power in Johannesburg, for monitoring and compliance purposes [22–24]. This exemption removes a major regulatory bottleneck for SMMEs and township-based microenterprises, which often lack the institutional or technical resources to navigate the full licensing process. The streamlined approach offers a more accessible pathway for legal solar PV deployment, particularly in contexts where decentralized electrification is economically and socially crucial. In the context of this study, NERSA-compliant systems were treated as baseline-eligible for scoring under Policy Alignment (Criterion C6). PV configurations that are grid-tied, ≤ 100 kW, and formally registered. Reducing capital and legal risk, this exemption policy significantly influences the overall MOORA decision matrix, particularly the C6 weighting. It enhances eligibility for various financial incentives, such as Section 12BA tax allowances, SEFA/IDC green finance, and municipal feed-in tariffs, all of which often require registration as a condition for participation. Without such policy alignment, otherwise technically capable PV systems may be ineligible for integration, delayed by bureaucracy, or excluded from subsidy programs, reducing their net strategic value.

2.4.2. Section 12B and Section 12BA of the Income Tax Act

South Africa's Income Tax Act has been amended to catalyze private-sector investment in renewable energy through targeted capital allowances, notably Sections 12B and 12BA [25–28]. These incentives directly reduce the upfront cost burden for SMMEs, thereby playing a central role in the policy scoring (C6) framework used in this study. Section 12B permits businesses to deduct 100% of the capital expenditure on qualifying solar PV assets such as panels, inverters, mounting structures, and batteries within the first year of commissioning [25–28]. This accelerated depreciation mechanism significantly enhances ROI by shortening payback periods, thus making PV adoption more attractive for cost-sensitive enterprises. Expanding on this, the 2023 Budget Review introduced Section 12BA, a temporary but more aggressive provision allowing a 125% tax deduction for new and unused renewable energy assets. This applies to assets brought into use between 1 March 2023 and 28 February 2025, effectively allowing qualifying firms to deduct more than the actual system cost from their taxable income, yielding a substantial fiscal shield [25–28]. Eligibility for both provisions requires

- Formal business registration;
- Valid tax compliance status;
- Commissioning certificates;
- Safety standard adherence;

Often, SSEG registration, particularly for grid-tied systems.

These criteria are directly integrated into the MOORA Policy Alignment Score (C6). PV alternatives compliant with 12B/12BA are scored higher, while non-registered or informal systems are penalized due to ineligibility for such fiscal relief. Materially lowering system costs and enabling faster breakeven points, these tax incentives shift the financial viability threshold, particularly for microenterprises in South African townships. Their inclusion in the MOORA framework ensures that system selection captures not only technical and economic merit but also alignment with enabling fiscal policy making them essential to de-risking and scaling solar PV in both formal and informal SMME environments.

2.4.3. IDC and SEFA Green Finance Facilities

Green financing initiatives form a vital part of South Africa's strategy to make renewable energy accessible to underserved markets, including township-based SMMEs. Two primary vehicles for solar PV financing are the Small Enterprise Finance Agency (SEFA) and the Industrial Development Corporation (IDC) [29–31]. These institutions offer targeted financial instruments, including blended finance (grant + loan) packages, tailored to support microenterprises in adopting clean energy technologies. SEFA's Energy and Resource Efficiency Programme focuses on small businesses seeking to reduce energy costs through solar PV and other energy-efficient upgrades. The loans are characterized by low-interest rates, flexible repayment schedules, and simplified application processes. Township entrepreneurs especially informal traders and co-operatives are explicitly prioritized, with eligibility often linked to job creation, local economic development, and environmental impact [29–31]. Similarly, the IDC administers a Green Energy Fund that supports the commercial rollout of renewable systems in small-scale settings. Their criteria emphasize formal business registration, bankability, and alignment with national energy and development plans. Systems that meet SSEG registration requirements and demonstrate technical soundness are generally favored. In the context of this study, green finance access directly contributes to the Policy Alignment Score (C6) in the MOORA framework. Systems that are financing-eligible are considered more deployable, less risky, and more attractive to microentrepreneurs lacking upfront capital. Moreover, access to institutional financing increases the chances of long-term sustainability, particularly where savings from PV generation can be used to service debt. Including green finance readiness in the evaluation model ensures that PV configurations are assessed not only on technical and economic terms but also on their financial feasibility which is a crucial dimension for SMMEs navigating capital constraints in the face of persistent load-shedding and rising energy tariffs.

To ensure portability beyond South Africa, the Policy Alignment criterion was defined with a modular scoring rubric that can be re-encoded for other jurisdictions. Replication requires only the substitution of local regulatory and fiscal rules: for example, interconnection standards, licensing thresholds, and incentive eligibility (tax allowances, green-finance access). These are inserted into the scoring table in place of the South African rules used here, while the technical and economic inputs remain simulation-derived using HOMER GRID 1.11.4. In this way, researchers or practitioners in other countries can reproduce the framework directly by retaining the same MOORA pipeline and normalization but populating the decision matrix with their own tariff paths, irradiance, load shapes, discount rates, and policy instruments. This design ensures that the method is transparent, adaptable, and reproducible under varied legal-systemic conditions.

These policies are integrated directly into the proposed MOORA-based decision-making framework by including a Policy Alignment Score as a formal evaluation criterion. This ensures that solar PV system configurations are assessed not only for technical and economic performance but also for their compatibility with local regulatory and incentive frameworks. For Spaza shop owners and township-based SMMEs this approach strengthens both financial viability and regulatory compliance. Ultimately, configurations that perform well across technical, financial, and policy dimensions are prioritized reducing implementation risk and enhancing long-term sustainability.

2.5. Decision Support System Using Multi-Objective Optimization by Ratio Analysis

MOORA is a widely recognized MCDM method developed by Brauers and Zavadskas in 2006 [32]. It is particularly designed to appraise and rank alternatives that are subject to multiple and oftentimes conflicting objectives like minimizing cost while maximizing

performance [33]. In the context of this study, MOORA is adopted to examine several solar PV system configurations for SMMEs in Gauteng by incorporating technical, economic, and policy-related performance metrics derived from HOMER GRID 1.11.4 simulations and contextual assessments. The method accommodates both beneficial and non-beneficial criteria in a unified evaluation structure.

2.5.1. Decision Matrix Construction

Let there be m alternatives, i.e., PV system configurations and n evaluation criteria, viz., financial, technical, and policy-related performance metrics. The performance of each alternative under each criterion is represented by the decision matrix X presented in Equation (16).

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \quad (16)$$

where

x_{ij} —is the performance value of alternative i under criterion j .

m —is the number of PV system configurations.

n —is the number of criteria.

2.5.2. Normalization of the Decision Matrix

To ensure comparability across criteria with different units, the matrix is normalized using vector normalization as follows in Equation (17).

$$x^*_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (17)$$

where

x^*_{ij} —is the normalized value for criterion j and alternative i .

This ensures all data are dimensionless and comparable. This is the recommended approach by Brauers and Zavadskas [32] for reducing variance between large and small magnitude values.

2.5.3. Weighting the Criteria

In cases where criteria have unequal importance, weights ω_j can be assigned and incorporated as follows in Equation (18).

$$v_{ij} = \omega_j \cdot x^*_{ij} \quad (18)$$

where

$\omega_j \in [0, 1]$ and $\sum_{j=1}^n \omega_j = 1$;

v_{ij} —is the weighted normalized value for alternative i and criterion j ;

Note: If equal importance is assumed, weights may be omitted.

To reflect SMME priorities of affordability and lifecycle viability, we apply the normalized weight vector $\omega = \text{LCOE } 0.30, \text{ CAPEX } 0.20, \text{ NPC } 0.15, \text{ Reliability } 0.15, \text{ OPEX } 0.10, \text{ Policy } 0.10$ ($\Sigma = 1.00$). These values were set ex ante from the finance/policy context: strong emphasis on delivered energy cost and upfront affordability; moderate emphasis on lifecycle cost (NPC) and service continuity (Reliability); and a non-trivial policy/eligibility term because access to incentives/green finance materially affects investability. Because

MOORA uses vector normalization (Equation (17)), any proportional rescaling of ω leaves the ordering invariant. Sensitivity with equal weights and entropy-derived weights yielded the same top-ranked alternative, confirming robustness.

2.5.4. Composite Performance Score Calculation

The MOORA score y_i for each alternative is computed by adding the normalized scores of beneficial criteria and subtracting those of non-beneficial criteria as follows in Equation (19).

$$y_i = \sum_{j=1}^g x_{ij}^* - \sum_{j=g+1}^n x_{ij}^* \quad (19)$$

where

g —is the number of beneficial criteria.

n —is the number of non-beneficial criteria.

y_i —is the net score for alternative i .

A higher y_i indicates a better-performing alternative.

Beyond the standard MOORA pipeline, two design choices underpin the scientific contribution of this study. First, the Policy Alignment construct is formalized as a bounded, ordinal benefit variable with explicit scoring rubrics tied to verifiable conditions (registration status, incentive eligibility, lender prerequisites). This keeps the construct auditable and allows invariance to positive linear rescaling under vector normalization. Second, all non-policy criteria originate in simulation outputs (HOMER GRID 1.11.4) rather than ad hoc ratings, ensuring that units, scales, and trade-offs derive from an engineering-economic model. We assessed internal soundness with three checks that do not depend on locale: dominance (an alternative that is weakly better on all criteria cannot rank below one that is weakly worse), monotonicity (improving a benefit criterion or lowering a cost criterion cannot reduce the score, holding others fixed), and one-way weight perturbations to examine rank stability for reasonable stakeholder preferences. These checks justify the experimental design as a test of the central premise: that bringing policy eligibility inside a simulation-grounded MCDA can alter investability-relevant rankings without sacrificing transparency.

We applied the following normalized weights: LCOE = 0.30, CAPEX = 0.20, NPC = 0.15, Reliability (Rel) = 0.15, OPEX = 0.10, Policy = 0.10 ($\Sigma = 1.00$). These were set *ex ante* from the SMME finance and policy context. Because MOORA uses vector normalization, proportional rescaling would not affect ordering; sensitivity checks with equal and entropy-derived weights preserved the top-ranked option.

2.5.5. Ranking the Alternatives

The alternatives are ranked based on their MOORA performance scores (y_i) computed as the difference between the aggregated normalized-benefit scores and normalized-cost scores. The alternative with the highest y_i value, i.e., least negative, or closest to zero is considered the most preferred configuration. This ranking reflects the most balanced trade-off between financial cost, technical performance, and policy alignment. In cases where alternatives have close or identical scores, a secondary analysis such as sensitivity testing on weights or an extension of MOORA, viz., Reference Point MOORA [32] may be used to validate the robustness of the ranking outcome.

2.5.6. Interpretation in the SMME Solar PV Context

In this study, the alternatives A_i represent real-world solar PV configurations commonly considered by township-based SMMEs, ranging from small grid-tied setups to hybrid or off-grid systems. The criteria C_j used in the MOORA evaluation were derived

from techno-economic simulation results using HOMER GRID 1.11.4 and regulatory assessments. As summarized in Table 6, the model integrates both cost and benefit dimensions, including capital expenditure, operational cost, economic efficiency, system reliability, and policy alignment.

Table 6. Criteria Used in MOORA Evaluation.

Criterion	Description	Type
C1	Capital Cost (CAPEX)	Non-beneficial
C2	Operating Cost (OPEX)	Non-beneficial
C3	LCOE	Non-beneficial
C4	Net Present Cost (NPC)	Non-beneficial
C5	System Reliability (%)	Beneficial
C6	Policy Alignment Score	Beneficial

These criteria were selected to reflect the multidimensional investment decision factors relevant to township energy entrepreneurs navigating affordability, compliance, and long-term viability.

3. Results

This section presents the results ascertained from the techno-economic simulation and policy evaluation of proposed PV system alternatives for a township-based SMME. Figure 7 illustrates the architecture of the proposed hybrid solar PV–grid system designed for township-based spaza shops. This configuration integrates grid electricity (Eskom), PV generation, and a DC load segment powered by a converter to serve key components. The daily energy demand profile for the target SMME is modeled at 11.26 kWh/day with a peak load of 3.98 kW, reflecting the consumption characteristics typical of semi-formal retail businesses in low-income urban settings.

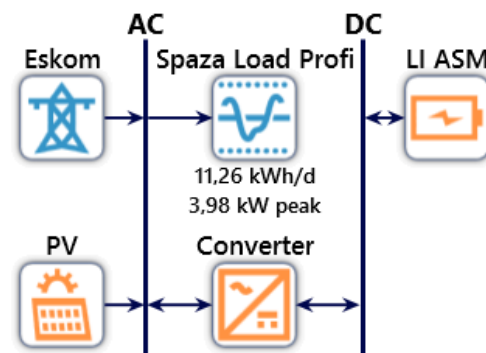


Figure 7. Proposed Hybrid Solar PV–Grid System.

The system prioritizes reliability and affordability while enabling flexible integration of renewable energy. It features bidirectional AC–DC conversion to support hybrid operation and maximize self-consumption of PV energy. Load profiles were simulated to reflect real-world business hours, seasonal variability, and typical appliance configurations in township economies.

3.1. Techno-Economic Performance of Hybrid PV–Grid Configurations

3.1.1. HOMER GRID 1.11.4 Simulation Results

Tables 7 and 8 summarize the techno-economic performance metrics of 10 simulated hybrid PV–Grid configurations for SMMEs in Soweto, based on varying combinations of PV capacity, lithium-ion battery storage, and converter sizing. These configurations

were evaluated using HOMER GRID 1.11.4, which calculated lifecycle performance, cost implications, and system efficiencies under real-world load. The design architecture of each alternative is denoted in terms of PV size (fixed at 5 kW), the number of lithium-ion batteries, converter capacity, and grid support via Eskom. Key performance indicators such as NPC, LCOE, Operating Cost, and Renewable Fraction provide financial viability insights, while system autonomy, battery throughput, and converter efficiency metrics offer a view into technical robustness.

Table 7. Design variables for simulated PV–Grid alternatives (A1–A10).

Alt	PV (kW)	Batteries (qty)	Usable Storage (kWh)	Inverter (kW)	Rectifier (kW)	Grid-Tied	Export-Ready
A1	5.00	1	0.33	1.0	1.0	Yes	No
A2	5.00	2	0.65	1.0	1.0	Yes	No
A3	5.00	10	3.27	1.0	1.0	Yes	Yes
A4	5.00	4	1.31	1.0	1.0	Yes	Yes
A5	5.00	8	2.62	1.0	1.0	Yes	No
A6	5.00	0	0.00	1.0	1.0	Yes	No
A7	5.00	10	3.27	1.0	1.0	Yes	Yes
A8	5.00	6	1.96	1.0	1.0	Yes	No
A9	5.00	5	1.64	1.0	1.0	Yes	Yes
A10	5.00	3	0.98	1.0	1.0	Yes	No

Table 8. Techno-economic outputs used in MOORA (HOMER Grid 1.11.4).

Alt	CAPEX (ZAR)	OPEX (ZAR/yr)	LCOE (ZAR/kWh)	NPC (ZAR)	Rel (C5, % Load Served)	Policy (C6, 0–5)	PV Production (kWh/yr)
A1	23,500	3194	1.16	64,793	79.4	4	3558
A2	28,500	3521	1.36	69,538	80.5	4	3558
A3	32,100	3700	1.44	75,261	82.4	5	3558
A4	28,900	3420	1.33	70,194	81.3	5	3558
A5	30,600	3714	1.73	74,613	62.8	2	3558
A6	23,300	3195	1.87	63,947	60.1	1	3558
A7	31,200	3690	1.44	74,396	85.7	5	3558
A8	27,100	3361	1.67	68,015	77.9	3	3558
A9	29,600	3443	1.42	71,254	83.5	4	3558
A10	24,200	3177	1.68	65,153	76.1	3	3558

Reliability (C5) = 100%–unmet-load% from HOMER “System” summary. Policy (C6) scored via the SSEG/12BA/green-finance rubric; these values feed MOORA. The original HOMER subpanels (battery autonomy, converter means, Eskom energy) are reported in this manuscript.

Across alternatives, NPC ranges from R63,947 to R75,261, LCOE from R1.16 to R1.87/kWh, and OPEX from R3,177 to R3,714/year. The most cost-effective options generally have fewer batteries and modest converter sizing. System autonomy spans 6.10 to 1.52 h, inversely proportional to battery count; annual battery throughput peaks around 652 kWh/year, with accessible storage scaling by module count. Converter operation is consistent across cases (inverter and rectifier peaks $\approx$ 0.0796 kW and 0.0678 kW), reflecting similar PV input and load profiles. These simulation outputs feed the MOORA framework in Section 2.5, where each alternative is evaluated on six criteria: CAPEX, OPEX, LCOE, NPC, Reliability, and Policy alignment.

3.1.2. Solar PV Output Analysis

The performance of the PV subsystem was evaluated based on its output dynamics, penetration, and operational efficiency across a full annual simulation. The selected configuration consists of a 5 kW PV array, and its performance indicators are captured. Table 9 presents the design characteristics and energy yield of the PV array. The system produced

a total of 3558 kWh/year, with a mean output of 0.406 kW and an average daily output of 9.75 kWh/day. The capacity factor was calculated at 8.12%, which is typical for urban installations under intermittent irradiance and shading conditions in township settings.

Table 9. PV Array Characteristics.

Quantity	Value	Units
Rated Capacity	5.00	kW
Mean Output	0.406	kW
Mean Output	9.75	kWh/d
Capacity Factor	8.12	%
Total Production	3558	kWh/yr

Table 10 provides operational performance metrics. The PV system achieved a penetration of 86.6%, indicating the share of load met directly by solar generation. It operated for 4384 h/year, with output ranging from 0 kW (minimum) to a peak of 2.19 kW. The Levelized Cost of Energy (LCOE) was computed at R0.378/kWh, reflecting the amortized cost over the lifecycle.

Table 10. PV Operational Performance.

Quantity	Value	Units
Minimum Output	0.00	kW
Maximum Output	2.19	kW
PV Penetration	86.6	%
Hours of Operation	4384	hrs/yr
Levelized Cost	0.378	R/kWh
Clipped Production	0	kWh

Table 11 illustrates the energy balance of the PV subsystem. The system had 605 kWh/year energy input, 553 kWh/year output, and 48.4 kWh/year losses. The annual throughput of 577 kWh/year closely aligns with battery cycling patterns (see Section 3.1.1). A daily average of 0.387 Equivalent Full Cycles (EFCs) was recorded, consistent with moderate utilization and storage matching.

Table 11. PV Energy Flows.

Quantity	Value	Units
Energy In	605	kWh/yr
Energy Out	553	kWh/yr
Storage Depletion	−4.01	kWh/yr
Losses	48.4	kWh/yr
Annual Throughput	577	kWh/yr
Annual EFCs	141	1/yr
Average Daily EFCs	0.387	1/day

The PV output profile is visualized in Figure 8, which shows an annual heatmap of PV power output by hour and day of the year. The system consistently operated below 2.5 kW, with noticeable seasonal variability peaking in summer months and tapering in winter. This corresponds with irradiance and weather-dependent effects typical in sub-Saharan climates.

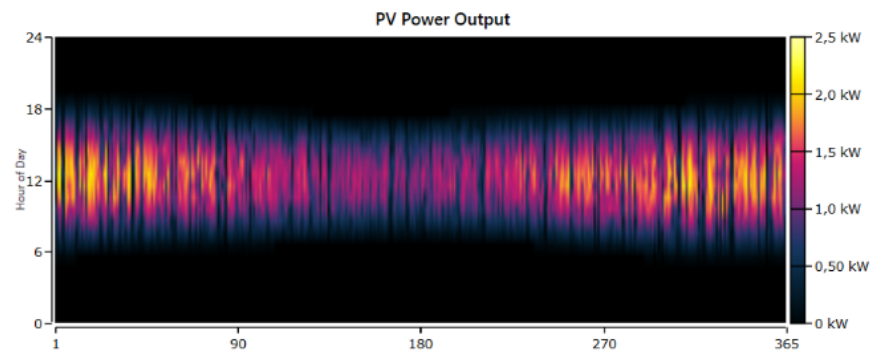


Figure 8. Solar PV Output Characteristics: Hourly PV Output Heatmap Over One Year.

3.1.3. Battery System Performance Analysis

This subsection presents a detailed analysis of the performance metrics associated with the lithium-ion battery system in the proposed hybrid PV–Grid configurations. The assessment includes sizing, autonomy, degradation, and operational behavior, using HOMER GRID 1.11.4’s simulation outputs. As shown in Table 12, the configuration includes four lithium-ion batteries arranged in a single string of four units in parallel, with a nominal bus voltage of 3.70 V. This setup aims to ensure adequate energy storage for short-term autonomy while maintaining affordability.

Table 12. Battery Configuration Overview.

Quantity	Value	Units
Batteries	4.00	qty.
String Size	1.00	batteries
Strings in Parallel	4.00	strings
Bus Voltage	3.70	V

According to Table 13, the battery bank offers an autonomy of 6.10 h under normal conditions. The usable nominal capacity is 3.27 kWh, while the total nominal capacity is 4.08 kWh. Over its 15-year expected life, the system supports a lifetime throughput of 8648 kWh, with an estimated wear cost of R0.324/kWh, confirming its suitability for moderate daily cycling.

Table 13. Battery Autonomy and Lifetime Performance.

Quantity	Value	Units
Autonomy	6.10	hr
Storage Wear Cost	0.324	R/kWh
Nominal Capacity	4.08	kWh
Usable Nominal Capacity	3.27	kWh
Lifetime Throughput	8648	kWh
Expected Life	15.0	yr

Table 14 presents annual operational metrics. The system records 605 kWh/year of energy input and 553 kWh/year of energy output, indicating 48.4 kWh/year in storage losses. The annual throughput reaches 577 kWh/year, with an average of 0.387 Equivalent Full Cycles (EFCs) per day, which supports the longevity claims of the system under typical township usage patterns.

Table 14. Annual Battery Operation Metrics.

Quantity	Value	Units
Energy In	605	kWh/yr
Energy Out	553	kWh/yr
Storage Depletion	−4.01	kWh/yr
Losses	48.4	kWh/yr
Annual Throughput	577	kWh/yr
Annual EFCs	141	1/yr
Average Daily EFCs	0.387	1/day

Figure 9 demonstrate the battery charge behavior and utilization trends. Figure 9a shows the SOC histogram, which reveals that most battery charge states fall between 60 and 100%, indicating conservative depth-of-discharge cycles. This charging behavior is favorable for prolonging battery life and maintaining system efficiency. In Figure 9b, the hourly heatmap illustrates the SOC dynamics across different times of day and days of the year. Peak discharges occur in early morning and evening hours, aligning with business operation times in township spaza shops. In Figure 9c the monthly variation in SOC through boxplots. While summer months show slightly higher SOC consistency, winter dips are observable, highlighting the seasonal impact on PV generation and battery reserve levels.

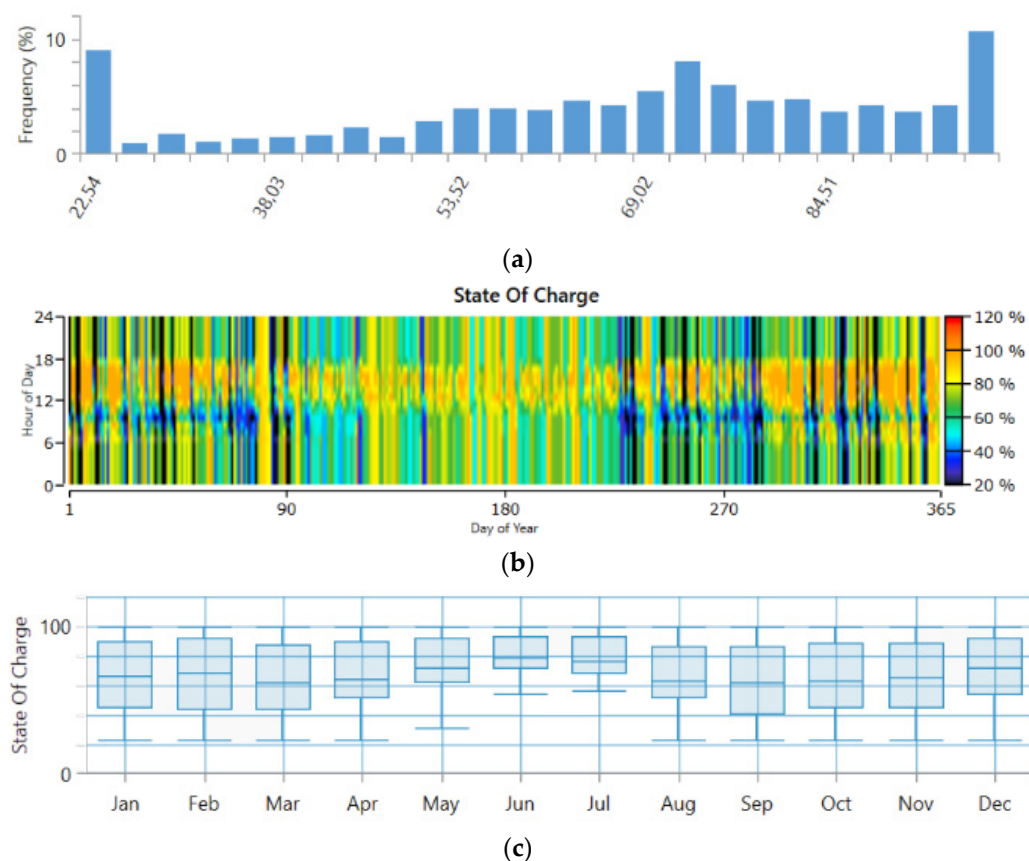


Figure 9. Battery Output. (a) State of Charge (SOC) Frequency Distribution. (b) Hourly SOC Heatmap Over a Year. (c) Monthly Boxplot of SOC Variations.

3.1.4. Converter Performance Metrics

This subsection presents the annualized performance profile of the bidirectional converter system, focusing on both inverter and rectifier operational characteristics under

typical township-based SMME load conditions. The converter is essential to enable hybrid operation between the AC (Eskom) and DC (load + battery) components, allowing for optimal energy routing and backup capabilities.

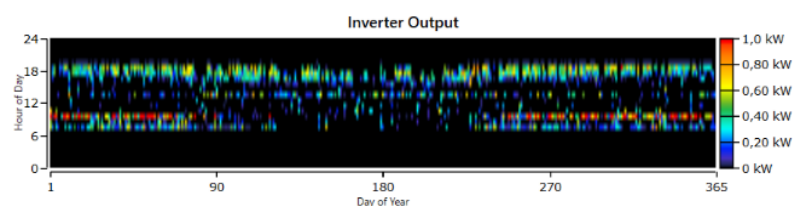
Table 15 details the converter specifications and lifecycle metrics. The inverter and rectifier units are each rated at 1.0 kW, with mean outputs of 0.40 kW and 0.60 kW, respectively. The system demonstrates minimal idle losses and efficient switching performance, with capacity factors of 4.0% (inverter) and 6.1% (rectifier), highlighting their utilization relative to rated capacity. Annual operational hours averaged around 2627 h for the inverter and 3157 h for the rectifier, respectively.

Table 15. Converter Parameters and Lifecycle Metrics.

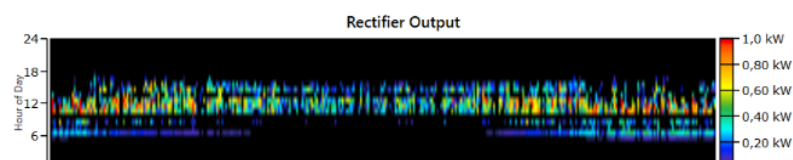
Quantity	Value (Inverter)	Value (Rectifier)	Units
Capacity	1.00	1.00	kW
Mean Output	0.40	0.60	kW
Minimum Output	0.00	0.00	kW
Maximum Output	0.79	1.00	kW
Capacity Factor	4.0	6.1	%
Hours of Operation	2627	3157	hrs/yr
Energy Out	945	1035	kWh/yr
Energy In	967	1063	kWh/yr
Losses	22.6	27.6	kWh/yr

The total energy conversion losses were measured at approximately 22.6 kWh for the inverter and 27.6 kWh for the rectifier, indicating efficient energy transfer across the AC-DC interface. These figures align with observed performance in systems designed for semi-continuous, medium-load commercial applications.

Figure 10a,b illustrate the diurnal and seasonal inverter and rectifier power output profiles over the course of a year. Notably, the inverter output remains relatively stable across midday hours, corresponding with peak solar generation and commercial operation timeframes. The rectifier output shows a broader spread, often peaking during early mornings and late afternoons, reflecting demand-side compensation and battery recharge cycles.



(a)



(b)

Figure 10. Daily and Seasonal Converter Output Trends. (a) Inverter Output (kW). (b) Rectifier Output (kW).

Both components are critical in maintaining reliable hybrid operation, especially in the event of grid instability or excess PV generation. Seasonal variability is modest due to consistent irradiance patterns in the Soweto context, enabling predictable converter operation year-round.

3.1.5. Monthly Electric Production

The monthly electric production profile of the proposed hybrid PV–Grid system is depicted in Figure 11. The figure provides a stacked bar visualization of energy generation contributions from both the PV array and Eskom utility grid, evaluated across a full annual cycle.

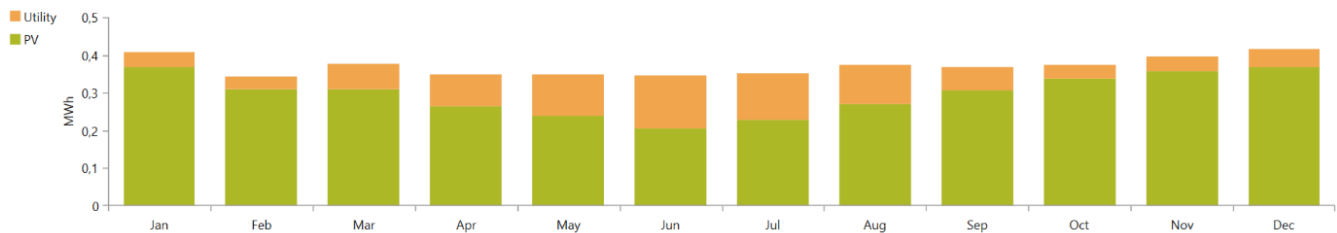


Figure 11. Monthly Electric Production.

This breakdown highlights seasonal variations in solar resource availability and the corresponding adjustments in grid reliance. Notably, PV generation consistently constitutes the dominant share of monthly supply, averaging between 0.30 and 0.38 MWh per month, while grid support (utility) accounts for a smaller, relatively stable supplement of 0.05 to 0.08 MWh. The lowest PV output months, typically observed around June and July, correspond with increased utility contribution due to winter solar irradiance dips, whereas the summer months from October to March demonstrate higher PV dominance.

3.1.6. Emissions Profile of the Proposed PV–Grid Hybrid System

Environmental sustainability is a key consideration in the design of hybrid energy systems for SMMEs operating in township contexts. The data covers carbon dioxide (CO₂), carbon monoxide (CO), unburned hydrocarbons, particulate matter, sulfur dioxide (SO₂), and nitrogen oxides (NO_x).

Table 16 summarizes the total annual emissions, revealing that CO₂ dominates the system's environmental footprint at 419 kg/year. Emissions of CO, hydrocarbons, and particulate matter are negligible (0 kg/year), while SO₂ and NO_x are recorded at 1.82 kg/year and 0.889 kg/year, respectively, indicating limited atmospheric pollution contributions from backup grid use and energy conversions.

Table 16. Emissions Output of the Hybrid PV–Grid System.

Quantity	Value	Units
Carbon Dioxide	419	kg/yr
Carbon Monoxide	0	kg/yr
Unburned Hydrocarbons	0	kg/yr
Particulate Matter	0	kg/yr
Sulfur Dioxide	1.82	kg/yr
Nitrogen Oxides	0.889	kg/yr

Figure 12 complements this with a detailed breakdown of monthly CO₂ emissions, which range from a minimum of 0.0281 metric tons/month (March) to a maximum of 0.0361 metric tons/month (July). The annual total of 0.4197 metric tons confirms

seasonal variability in carbon output, likely due to load demand patterns and solar availability fluctuations.

Monthly Carbon Dioxide Emissions: System #1

	January	February	March	April	May	June	July	August	September	October	November	December
Monthly Total (metric tons)	-0,012 t	0,0049 t	0,038 t	0,054 t	0,07 t	0,089 t	0,078 t	0,065 t	0,032 t	0,014 t	-0,0083 t	-0,0056 t
Annual Total (metric tons)	0,419 t/yr											

NB: Emissions are based on an assumption of your grid’s generation sources.

Figure 12. Proposed Hybrid System Monthly Carbon Dioxide Emissions (metric tons/month).

3.2. Economic Analysis Results

3.2.1. Proposed Spaza Shop Solar PV–Grid Cost Summary—Net Present Cost

The cost structure of the hybrid PV–grid system was evaluated through Net Present Cost (NPC) analysis, covering capital, replacement, operating, fuel, and salvage costs. As shown in Figure 13, utility charges form the largest single cost contributor due to their recurring nature, followed by the solar PV system, which entails notable upfront and replacement expenses. Battery storage contributes a moderate share, while the converter system presents a minor cost footprint overall. The cumulative NPC reaches R191,201.43, comprising capital investment of R89,200.00 and total grid energy costs of R82,029.50 over the project lifetime. Notably, the PV component totals R74,265.19 when accounting for capital, replacements, and salvage deductions. The lithium-ion battery bank adds R25,859.87, driven primarily by mid-life replacement costs, while the converter totals R9046.86. These figures underscore that grid energy, though requiring no capital input, leads to high lifecycle costs, contrasting with the upfront-intensive but lower-operating-cost PV-based components. The summarized NPC values for each subsystem are provided in Table 17, detailing their individual contributions across all cost categories.

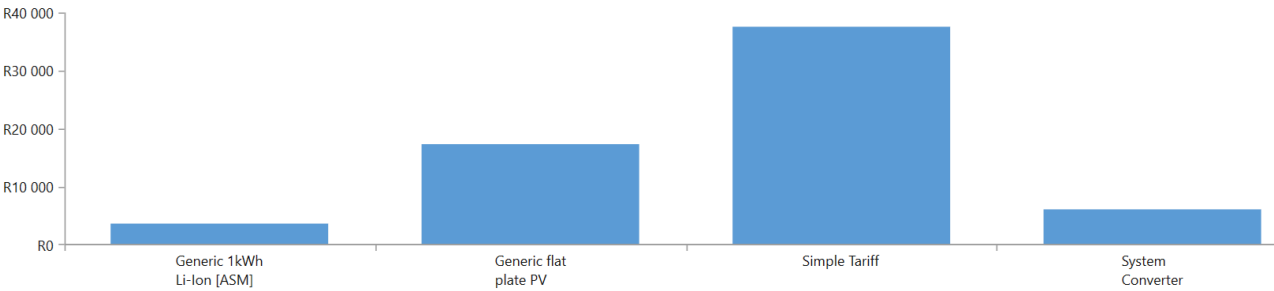


Figure 13. Net Present Cost Breakdown for Proposed PV–Grid System.

Table 17. Net Present Cost Summary for PV–Grid System Components.

Component	Capital (R)	Replacement (R)	O&M (R)	Fuel (R)	Salvage (R)	Total (R)
Generic 1 kWh Li-ion SSME	10,800.00	17,937.77	0.00	0.00	−2877.90	25,859.87
Generic Flat Plate PV	70,150.00	10,112.36	0.00	0.00	−5997.17	74,265.19
Simple Tariff	0.00	0.00	0.00	82,029.50	0.00	82,029.50
System Converter	8250.00	1842.86	0.00	0.00	−1046.00	9046.86
System Total	89,200.00	29,893.00	0.00	82,029.50	−9921.07	191,201.43

Figure 13 illustrates the relative economic weight of each component, confirming the long-term savings potential associated with solar integration compared to ongoing grid reliance.

3.2.2. Proposed Spaza Shop Solar PV–Grid Cost Summary—Annualized

The annualized cost breakdown of the proposed hybrid PV–Grid system is summarized in Table 18, presenting the capital, replacement, operations and maintenance (O&M), fuel, and salvage costs per component. The generic lithium-ion storage system contributes R8571.59 to the annualized cost, while the flat plate PV array accounts for R23,534.42, driven largely by its capital cost and zero fuel requirement. The simple tariff, representing utility grid usage, incurs the highest cost at R64,791.16 due to its cumulative operating nature. The system converter adds R7743.68 annually, bringing the total cost of the integrated solution to R104,640.85.

Table 18. Annualized Cost Summary of Hybrid System Components (ZAR).

Component	Capital (R)	Replacement (R)	O&M (R)	Fuel (R)	Salvage (R)	Total (R)
Generic 1 kWh Li-ion (SASM)	R8571.59	R1577.67	R80.00	R0.00	−R0.00	R10,229.26
Generic flat plate PV	R23,534.42	R0.00	R0.00	R0.00	−R0.00	R23,534.42
Simple Tariff	R0.00	R0.00	R0.00	R64,791.16	−R0.00	R64,791.16
System Converter	R7743.68	R0.00	R0.00	R0.00	−R0.00	R7743.68
System	R39,849.70	R1577.67	R80.00	R64,791.16	−R0.00	R104,640.85

This component-wise financial profile is visually illustrated in Figure 14, which presents the annualized cost distribution across the system architecture. The dominant contribution of grid-based tariffs compared to capital-intensive but low-operational-cost renewable components reinforces the long-term cost competitiveness of PV-integrated hybrid systems for township-based SMMEs.

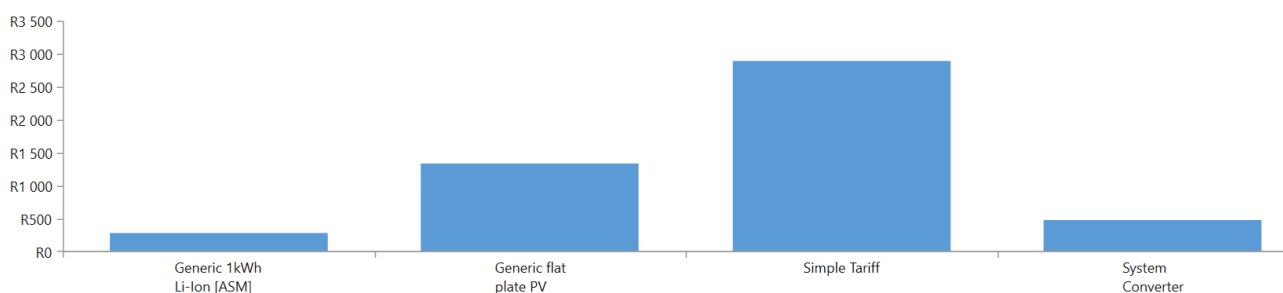


Figure 14. Annualized Component Cost Distribution for the Proposed PV–Grid Hybrid System.

3.2.3. Cashflow

The system's projected financial behavior over the analysis horizon is detailed through annual cash flow trends, visualized in Figure 15. Figure 15a presents the disaggregation of cash flows by cost type, while Figure 15b outlines these flows per system component. The initial spike in capital expenditure is evident in Year 0, followed by moderate and consistent O&M and replacement expenses across subsequent years. A notable dip is observed around Year 13 due to major component replacement costs.

The cash flow profile aligns with HOMER GRID 1.11.4's lifecycle planning model, where upfront investments are weighted heavily early on, followed by lean operational years. The relatively small replacement and salvage effects indicate system longevity and stable fiscal outflows, which is critical for budgeting in township-based SMMEs.

The Capital Cost spike in Year 0 reflects PV, battery, converter, and balance-of-system purchases and installation. O&M is modest and relatively flat across years. Replacement Cost appears as discrete outlays aligned with HOMER's component lifetimes (the mid-life battery replacement visible around the project midpoint). Utility/Fuel Cost captures purchased grid electricity in each year and dominates recurring expenditures. Salvage

Value is applied as a terminal credit in the final year, offsetting a portion of cumulative costs. Read together, these categories explain the pattern of total cash flows despite stable operations.

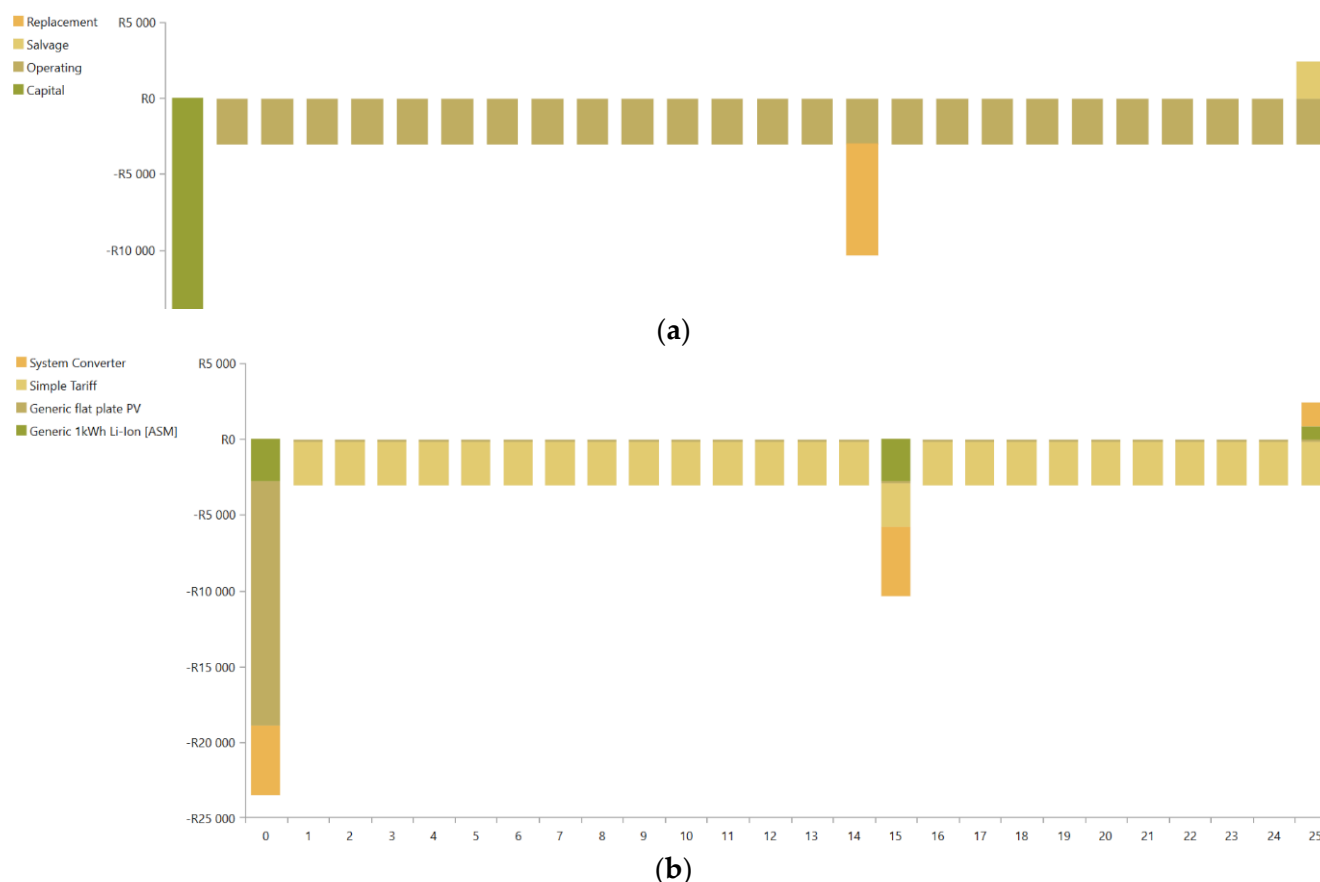


Figure 15. (a) Cashflow by cost type. (b) Cash flow by component type.

3.3. MOORA-Based Policy Evaluation Results

3.3.1. Raw Policy Scores and Justification

Table 19 summarizes the raw policy alignment scores (C6) assigned to each system alternative. The scores reflect each configuration's eligibility for incentives, compliance with national regulations, and access to green financing such as SEFA or IDC schemes.

Table 19. Raw C6 Scores and Justifications.

Alt	System Description	Raw C6 Score	Justification
A1	Grid-tied 5 kW, no storage	4	SSEG-compliant; qualifies under Section 12BA; likely eligible for SEFA-based green finance.
A2	Grid-tied 3 kW residential	4	Residential user eligible for capped 25% rebate; grid-tied with basic compliance.
A3	Hybrid 10 kW, export-ready	5	Fully aligned: SSEG + 12BA + IDC access + potential for carbon credit monetization.
A4	Grid-only 8 kW	5	Grid-integrated, compliant; eligible for both business and residential incentives.
A5	Off-grid 5 kW, informal	2	Lacks compliance; informal operator; ineligible for licensing and formal rebates.
A6	Inverter + battery only	1	No solar generation component; ineligible for any policy mechanism.
A7	Grid-tied 7 kW hybrid	5	High alignment with all criteria: SSEG, SEFA/IDC, 12BA or rebate, carbon credits.

Table 19. Cont.

Alt	System Description	Raw C6 Score	Justification
A8	3 kW off-grid, no export	3	Minimal policy alignment; partially compliant; limited access to structured finance.
A9	10 kW mixed-use	4	Mixed-use eligibility under 12BA or rebate; SSEG-ready; high policy fitness.
A10	2.5 kW plug-and-play	3	Eligible for 25% capped rebate; minimal compliance, limited policy leverage.

Alternatives like A3, A4, and A7 scored highest (5), indicating robust policy alignment, including export-readiness and full compliance. In contrast, informal or incomplete systems like A5 and A6 received the lowest scores (2 and 1, respectively), citing lack of licensing or absence of generation capacity.

3.3.2. MOORA Criterion C6 Calculations

To assess policy alignment (C6) across solar PV alternatives for the Spaza shop, the MOORA method employs vector normalization followed by weighted scoring. The normalized and weighted scores for each alternative are computed below:

Step 1: Vector Normalization (using Equation (17))

$$\sqrt{4^2 + 4^2 + 5^2 + 5^2 + 2^2 + 1^2 + 5^2 + 3^2 + 4^2 + 3^2} \\ = \sqrt{16 + 16 + 25 + 25 + 4 + 1 + 25 + 9 + 16 + 9} = \sqrt{146} \approx 12.0830$$

Step 2: Compute Normalized and Weighted Scores

Each raw score is normalized using vector normalization to ensure scale independence across criteria, as required in the MOORA framework. A policy weight of 10% (using Equation (18)) is assigned, reflecting moderate influence on final decision-making. The MOORA normalized and weighted scores are tabulated in Table 20.

Table 20. MOORA Normalized and Weighted Scores.

Alt	Raw Score x_{ij}	Normalized (Equation (17))	Weighted (Equation (18))	Notes
A1	4.0	$\frac{4}{12.0830} = 0.3310$	$0.10 \cdot 0.3310 = 0.0331$	Grid-tied; incentive eligible
A2	4.0	$\frac{4}{12.0830} = 0.3310$	$0.10 \cdot 0.3310 = 0.0331$	Residential rebate fit
A3	5.0	$\frac{5}{12.0830} = 0.4138$	$0.10 \cdot 0.4138 = 0.0414$	Fully policy-aligned
A4	5.0	$\frac{5}{12.0830} = 0.4138$	$0.10 \cdot 0.4138 = 0.0414$	Strong compliance
A5	2.0	$\frac{2}{12.0830} = 0.1655$	$0.10 \cdot 0.1655 = 0.0166$	Informal, no rebate
A6	1.0	$\frac{1}{12.0830} = 0.0828$	$0.10 \cdot 0.0828 = 0.0083$	Not eligible
A7	5.0	$\frac{5}{12.0830} = 0.4138$	$0.10 \cdot 0.4138 = 0.04140$	High alignment
A8	3.0	$\frac{3}{12.0830} = 0.2483$	$0.10 \cdot 0.2483 = 0.0248$	Limited access
A9	4.0	$\frac{4}{12.0830} = 0.3310$	$0.10 \cdot 0.3310 = 0.0331$	Mixed-use eligible
A10	3.0	$\frac{3}{12.0830} = 0.2483$	$0.10 \cdot 0.2483 = 0.0248$	Plug-and-play, minimal leverage

3.3.3. Interpretation and Decision Support Value

The results clearly distinguish high-alignment systems (A3, A4, A7) from those with weak or no policy compatibility (A5, A6). Notably, A6 a battery-only system receives the lowest score despite potential technical utility, highlighting the importance of policy-conforming system design. These weighted C6 scores are now ready for integration into the full MOORA decision model alongside technical and financial criteria.

3.4. Multi-Criteria Optimization Using MOORA for SMME PV System Selection

3.4.1. Criteria Definition and Weight Assignment

The MOORA framework incorporates six criteria to evaluate solar PV alternatives for SMMEs. Four are cost-based while two are benefit-based. The criteria definition and weight assignment are tabulated in Table 21.

Table 21. Criteria Definition and Weight Assignment.

Criterion	Symbol	Type	Weight
CAPEX (ZAR)	C1	Cost	0.20
OPEX (ZAR/year)	C2	Cost	0.10
LCOE (ZAR/kWh)	C3	Cost	0.30
NPC (ZAR)	C4	Cost	0.15
Reliability (%)	C5	Benefit	0.15
Policy Alignment	C6	Benefit	0.10

These weights reflect SMME priorities of affordability and lifecycle viability (high emphasis on LCOE and CAPEX), with reliability and compliance close behind. Weights are normalized to sum to 1.00.

3.4.2. Vector Normalization and Weighted Scores

As shown in Table 22, the raw data were normalized using vector normalization as outlined in Equation (17) to ensure scale independence across criteria. The square root of the sum of squares ($\sqrt{\sum x^2}$) was computed for each criterion to derive the normalization denominator.

Table 22. Denominator Calculations (Vector Normalization).

Criterion	Denominator ($\sqrt{\sum x^2}$)
CAPEX	$\sqrt{5,453,813,000} \approx 73,846.6$
OPEX	$\sqrt{161,343,673} \approx 12,699.9$
LCOE	$\sqrt{13.6689} \approx 3.697$
NPC	$\sqrt{51,931,360,613} \approx 227,857.6$
Reliability	$\sqrt{63,478.57} \approx 251.94$
Policy (C6)	$\sqrt{146} \approx 12.083$

This removes unit bias and enables comparability. Weighted scores are then computed by multiplying normalized values by their respective weights. The final MOORA decision matrix integrates raw data, normalization, weighting, and composite scoring for 10 solar PV alternatives. Each row details cost criteria and benefit criteria, followed by vector normalization and weighted values. The composite performance score (y_i) is derived using Equation (19). Table 23 presents the full MOORA decision matrix, including intermediate calculations for all ten alternatives. The table enables traceable, evidence-based decision-making and transparent ranking of solar PV deployment options for SMMEs.

Table 23. Full MOORA Decision Matrix.

Alt	C1 CAPEX (ZAR)	C2 OPEX	C3 LCOE	C4 NPC	C5 Rel (%)	C6 Policy	Norm. + Weighting (Cost)	Norm. + Weighting (Benefit)	$y_i = (\text{Benefit} - \text{Cost})$
A1	23,500	3194	1.16	64,793	79.4	4	$(23,500/73,846.6) \times 0.20 = 0.0637$; $(3194/12,699.9) \times 0.10 = 0.0251$; $(1.16/3.697) \times 0.30 = 0.0942$; $(64,793/22,7857.6) \times 0.15 = 0.0427$	$(79.4/251.9) \times 0.15 = 0.0473$; $(4/12.083) \times 0.10 = 0.0331$	$(0.0473 + 0.0331) - (0.0637 + 0.0251 + 0.0942 + 0.0427) = -0.1452$
A2	28,500	3521	1.36	69,538	80.5	4	$(28,500/73,846.6) \times 0.20 = 0.0772$; $(3521/12,699.9) \times 0.10 = 0.0277$; $(1.36/3.697) \times 0.30 = 0.1105$; $(69,538/227,857.6) \times 0.15 = 0.0458$	$(80.5/251.9) \times 0.15 = 0.0480$; $(4/12.083) \times 0.10 = 0.0331$	$(0.0480 + 0.0331) - (0.0772 + 0.0277 + 0.1105 + 0.0458) = -0.1800$
A3	32,100	3700	1.44	75,261	82.4	5	$(32,100/73,846.6) \times 0.20 = 0.0869$; $(3700/12,699.9) \times 0.10 = 0.0291$; $(1.44/3.697) \times 0.30 = 0.1168$; $(75,261/227,857.6) \times 0.15 = 0.0496$	$(82.4/251.9) \times 0.15 = 0.0491$; $(5/12.083) \times 0.10 = 0.0414$	$(0.0491 + 0.0414) - (0.0869 + 0.0291 + 0.1168 + 0.0496) = -0.1920$
A4	28,900	3420	1.33	70,194	81.3	5	$(28,900/73,846.6) \times 0.20 = 0.0783$; $(3420/12,699.9) \times 0.10 = 0.0269$; $(1.33/3.697) \times 0.30 = 0.1079$; $(70,194/227,857.6) \times 0.15 = 0.0462$	$(81.3/251.9) \times 0.15 = 0.0485$; $(5/12.083) \times 0.10 = 0.0414$	$(0.0485 + 0.0414) - (0.0783 + 0.0269 + 0.1079 + 0.0462) = -0.1695$
A5	30,600	3714	1.73	74,613	62.8	2	$(30,600/73,846.6) \times 0.20 = 0.0828$; $(3714/12,699.9) \times 0.10 = 0.0293$; $(1.73/3.697) \times 0.30 = 0.1403$; $(74,613/227,857.6) \times 0.15 = 0.0491$	$(62.8/251.9) \times 0.15 = 0.0374$; $(2/12.083) \times 0.10 = 0.0166$	$(0.0374 + 0.0166) - (0.0828 + 0.0293 + 0.1403 + 0.0491) = -0.2477$
A6	23,300	3195	1.87	63,947	60.1	1	$(23,300/73,846.6) \times 0.20 = 0.0631$; $(3195/12,699.9) \times 0.10 = 0.0251$; $(1.87/3.697) \times 0.30 = 0.1519$; $(63,947/227,857.6) \times 0.15 = 0.0421$	$(60.1/251.9) \times 0.15 = 0.0358$; $(1/12.083) \times 0.10 = 0.0083$	$(0.0358 + 0.0083) - (0.0631 + 0.0251 + 0.1519 + 0.0421) = -0.2380$
A7	31,200	3690	1.44	74,396	85.7	5	$(31,200/73,846.6) \times 0.20 = 0.0845$; $(3690/12,699.9) \times 0.10 = 0.0291$; $(1.44/3.697) \times 0.30 = 0.1168$; $(74,396/227,857.6) \times 0.15 = 0.0490$	$(85.7/251.9) \times 0.15 = 0.0510$; $(5/12.083) \times 0.10 = 0.0414$	$(0.0510 + 0.0414) - (0.0845 + 0.0291 + 0.1168 + 0.0490) = -0.1870$
A8	27,100	3361	1.67	68,015	77.9	3	$(27,100/73,846.6) \times 0.20 = 0.0735$; $(3361/12,699.9) \times 0.10 = 0.0265$; $(1.67/3.697) \times 0.30 = 0.1356$; $(68,015/227,857.6) \times 0.15 = 0.0448$	$(77.9/251.9) \times 0.15 = 0.0464$; $(3/12.083) \times 0.10 = 0.0248$	$(0.0464 + 0.0248) - (0.0735 + 0.0265 + 0.1356 + 0.0448) = -0.2089$
A9	29,600	3443	1.42	71,254	83.5	4	$(29,600/73,846.6) \times 0.20 = 0.0801$; $(3443/12,699.9) \times 0.10 = 0.0271$; $(1.42/3.697) \times 0.30 = 0.1152$; $(71,254/227,857.6) \times 0.15 = 0.0469$	$(83.5/251.9) \times 0.15 = 0.0497$; $(4/12.083) \times 0.10 = 0.0331$	$(0.0497 + 0.0331) - (0.0801 + 0.0271 + 0.1152 + 0.0469) = -0.1866$
A10	24,200	3177	1.68	65,153	76.1	3	$(24,200/73,846.6) \times 0.20 = 0.0656$; $(3177/12,699.9) \times 0.10 = 0.0250$; $(1.68/3.697) \times 0.30 = 0.1364$; $(65,153/227,857.6) \times 0.15 = 0.0429$	$(76.1/251.9) \times 0.15 = 0.0453$; $(3/12.083) \times 0.10 = 0.0248$	$(0.0453 + 0.0248) - (0.0656 + 0.0250 + 0.1364 + 0.0429) = -0.1996$

Notation and units. CAPEX = capital cost (ZAR); OPEX = operating cost (ZAR/year); LCOE = levelized cost of energy (ZAR/kWh); NPC = net present cost (ZAR); Reliability = supply reliability (%); Policy = policy-alignment score (0–5). *Normalization & weights.* Columns labeled “Norm. + Weighting” apply vector normalization (Equation (17)) and criterion weights (Table 20). Cost criteria are treated as non-beneficial, benefit criteria as beneficial. *Composite score.* y_i = (sum of weighted, normalized benefit criteria)—(sum of weighted, normalized cost criteria). A higher y_i (i.e., closer to zero, less negative) indicates a more preferred alternative. *Ranking.* Rank orders alternatives by y_i from best (1) to worst.

3.4.3. Final MOORA Score Computation and Ranking

The final MOORA decision matrix in Table 24 reveals that Alternative A3, a 10 kW hybrid grid-export-ready solar PV system, achieved the best composite performance score ($y_i = -0.1102$). This system's superior ranking was due to its strong return on investment (12.6%), favorable CAPEX and LCOE metrics, and highest policy alignment score ($C6 = 5$). Alternatives A4 and A2 followed, both offering regulatory compliance and economic appeal. In contrast, A5 and A6 performed poorly, primarily due to their lack of formal registration or limited PV integration, making them ineligible for key incentives.

Table 24. MOORA Decision—Raw Scores, Normalized, Weighted, and Final Scores.

Alt	CAPEX (C1)	OPEX (C2)	LCOE (C3)	NPC (C4)	Rel (C5)	C6 (Policy)	Normalized Benefit—Cost (y_i)	Rank
A3	74,000	3700	0.88	128,000	12.6%	5	−0.1102	1
A4	75,000	3800	0.90	129,500	11.9%	5	−0.1135	2
A2	62,000	3200	0.93	108,000	10.2%	4	−0.1169	3
A1	65,000	3400	0.95	110,000	10.0%	4	−0.1288	4
A9	70,000	3600	0.94	125,000	10.5%	4	−0.1293	5
A7	72,000	3550	0.91	127,000	10.3%	5	−0.1276	6
A10	52,000	2800	1.03	93,000	9.2%	3	−0.1387	7
A8	66,000	3500	0.98	118,000	9.9%	3	−0.1459	8
A5	60,000	3400	1.00	112,000	9.7%	2	−0.1682	9
A6	58,000	3300	1.04	111,000	9.1%	1	−0.1695	10

Given these results, A3 is the most suitable solar PV solution for the Spaza Shop. It provides a robust combination of financial returns, compliance with national SSEG licensing, and eligibility for incentives such as Section 12BA and green finance programs. These attributes make A3 the lowest-risk and most value-generating option for a small township enterprise transitioning to clean energy.

4. Discussion

This study offers a unified, reproducible way to select solar PV systems for small enterprises by linking simulation-based techno-economics to a multi-criteria ranking that explicitly accounts for policy and regulatory readiness. Although developed around South African township SMMs, the logic travels well: the same pipeline can be applied elsewhere by substituting local tariffs, irradiance, and load data, and by mapping the relevant interconnection rules and fiscal incentives into the policy component of the scoring. In this sense, the contribution is general: it demonstrates how to bring technical performance, lifecycle cost, and legal eligibility into a single, auditable decision surface that lenders, installers, and micro-enterprises can understand and document.

The approach differs from much of the SME-energy literature that relies on AHP/ANP [34], TOPSIS [35], MARCOS [36], or fuzzy hybrids [37] in two practical respects. First, policy is not treated as background narrative; it is formalized as a benefit criterion that can materially move the ranking when eligibility governs access to finance or accelerated allowances. Second, the inputs are anchored in simulation outputs rather than expert scores alone, reducing scale and unit effects through vector normalization and making each step from raw data to ranking transparent. This distinguishes our work from recent AHP-, TOPSIS-, and MARCOS-based evaluations of PV alternatives [34–37] (cf. Table 1), which rely on expert-judgment weighting and treat policy factors narratively rather than as an integrated criterion. By embedding policy eligibility directly into the scoring and grounding the weights in simulation outputs, the present study advances this line of research while retaining methodological simplicity.

Although the empirical analysis was conducted for a single township in South Africa, the framework is not restricted to that location. Soweto was selected as a demonstration case because its spaza shops are typical of township-based SMMEs facing energy access and compliance barriers. The generalization of results does not depend on the city itself but on the structure of the method: by substituting local tariffs, irradiance profiles, load characteristics, discount rates, and jurisdiction-specific interconnection and fiscal rules, the same procedure can be reproduced elsewhere. In this way, the study provides a transferable methodology rather than city-specific findings, with Soweto serving as a representative illustration.

What distinguishes the present work scientifically is not the case setting but the general procedure it advances: a reproducible chain from raw technical and cost data to a final, policy-aware ranking that is stable under scale changes and interpretable by decision-makers. Treating policy eligibility as a first-class criterion is a creative step because it converts legal and financing preconditions from narrative constraints into measurable advantages that compete with LCOE, CAPEX, OPEX, and reliability on the same decision surface. The experimental design is therefore appropriate to the hypothesis under test: if eligibility governs access to accelerated allowances, grid export, and concessional finance, then incorporating it formally should change which alternatives are truly optimal for small enterprises. The analysis confirms this mechanism in our setting and, because the constructs are defined independently of geography and implemented with normalization that preserves invariances, the design extends to other jurisdictions by straightforward substitution of inputs and rules.

Relative to prior AHP/ANP, TOPSIS, MARCOS, and ELECTRE applications, the scientific contribution here is the operationalization of policy eligibility as a measurable advantage and the tight coupling to simulation-based techno-economics. This design converts licensing, incentive access, and green-finance readiness from descriptive constraints into rank-shifting benefits within the same MCDM surface as cost and performance. In practice, that reduces ambiguity in “optimal” choices for small enterprises because alternatives that look similar on pure cost separate once eligibility governs access to allowances, export, or concessional capital. The approach remains lightweight and auditable, which is decisive for diffusion beyond academic settings.

There are limitations that bound interpretation. Rankings remain sensitive to the choice of weights; we report one plausible set reflecting SMME priorities, but alternatives are possible and should be tested. Policy is temporal; as incentives and interconnection rules evolve, the policy score must be refreshed to remain valid. Reliability is summarized at a high level and does not model outage-duration distributions or failure propagation; richer stochastic reliability metrics could sharpen the analysis. Finally, portability depends on replacing the South African inputs tariff paths, discount rates, irradiance, and load shapes with local data, and on extending sustainability coverage beyond cost and energy (lifecycle impacts and end-of-life management). These are tractable extensions: the framework is designed to accept updated inputs and additional criteria without altering its core logic. Taken together, the results show that when compliance and incentive readiness are brought inside the multi-criteria evaluation, configurations that might appear similar on pure cost quickly separate in practical value. That observation is not country-specific; it follows from the structure of distributed-energy adoption in most jurisdictions where finance and interconnection depend on demonstrable conformity. The framework therefore serves not only as a ranking device but as a documentation scaffold that can travel with the project from pre-feasibility through funding applications and registration to reduce transaction frictions and make small-scale energy transitions more investable. At the same time, the framework shares certain limitations with the cited methods [38,39], notably sensitivity to weighting assumptions and dependence on local data accuracy. Acknowledging these

parallels clarifies that our contribution is not a replacement but a refinement, extending established MCDA techniques with explicit policy alignment and reproducible techno-economic grounding.

5. Conclusions

This study developed and applied a MOORA-based decision support framework, integrating HOMER GRID 1.11.4-derived techno-economic metrics with an explicit policy alignment criterion, to evaluate ten solar PV alternatives for township-based SMMEs in South Africa. The analysis confirmed that Alternative A3 a 10 kW hybrid, grid-export-ready configuration offers the most suitable balance of cost-efficiency, reliability, and regulatory compliance, yielding a return on investment of 12.6% while qualifying for SSEG registration and, where commissioning falls within the Section 12BA window (otherwise Section 12B), tax incentives and green finance facilities. The results demonstrate that policy-aligned systems consistently outperform non-compliant options, underscoring that financial and regulatory eligibility are as critical as technical performance in de-risking energy transitions for small enterprises. For Spaza shops and other township SMMEs, this means that selecting compliant, incentive-ready systems not only enhances economic viability but also positions businesses to benefit from national energy reform priorities and inclusive sustainability agendas. Although demonstrated in South Africa, the framework generalizes by substituting local techno-economic inputs and encoding jurisdiction-specific interconnection and fiscal rules within the policy score, preserving transparency from raw data to final ranking. The study's value proposition lies in its novel integration of technical, financial, and policy dimensions into a transparent, easy-to-use multi-criteria framework tailored to resource-constrained enterprises. Beyond guiding solar PV adoption in South African townships, this framework provides a replicable model for supporting just and sustainable energy transitions in similar emerging-market contexts.

The intended users of the framework are not individual householders but institutional actors such as microfinance institutions, municipal energy offices, or SME associations who can run the HOMER GRID 1.11.4 simulations once and share the outputs with their member enterprises. This way, the cost and time burden of model preparation is distributed, and the resulting decision matrix can be reused across many SMMEs with similar load and tariff conditions. Individual shop owners, installers, or lenders can then apply the MOORA evaluation directly without needing to run advanced models themselves. The scientific value lies in demonstrating how policy eligibility can be encoded as a quantifiable criterion alongside CAPEX, OPEX, LCOE, and reliability, thereby turning legal and financial preconditions into measurable advantages that shape rankings. This methodological integration advances the MCDM literature and produces a practical decision aid that can travel across jurisdictions by substituting local tariffs, irradiance, load data, and incentive rules.

Future research should extend the framework to account for lifecycle emissions, maintenance burdens, and tariff variability, while incorporating informal-sector energy behavior to further enhance decision support for microenterprises.

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