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Optimization of 2200 WP Solar Power Components for EV Charging Using SMART Method

Rani Nopriyanti[a], Heri Setiawan[a], Iwan Harianton[a], Antonius Adi Seotopo[a], M. Sadiyo[a], Dimas Nugroho[a], Ryan Nur Iman[b], Ganis Sanhaji[c,*]

[a]Department of Manufacturing Engineering, Bandung Manufacturing Polytechnic, Bandung, 40135, Indonesia
[b]Department of Material Chemistry, Kanazawa University, Ishikawa, 920-1164, Japan
[c]Department of Manufacturing Design Engineering, Bandung Manufacturing Polytechnic, Bandung, 40135, Indonesia
*Corresponding Author: ganis.sanhaji@polman-bandung.ac.id

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ABSTRACT

The performance, efficiency, and lifetime of off-grid photovoltaic (PV) systems are strongly influenced by the appropriate selection of key components, including solar panels, charge controllers, batteries, and inverters. This study aims to determine the optimal configuration of a 2200 Wp off-grid PV system for an electric vehicle charging station at Bandung Polytechnic of Manufacturing (Polman Bandung). A Decision Support System based on the Simple Multi-Attribute Rating Technique (SMART) was employed to evaluate multiple technical and functional criteria across several component alternatives. A total of 8 alternatives, consisting of 2 alternatives for each component, were quantitatively assessed using weighted criteria and preference scores to obtain a final ranking. The results indicate that the optimal configuration consists of monocrystalline solar panels, an MPPT charge controller, LiFePO4 batteries, and a pure sine wave inverter, achieving the highest overall utility value. The system produced an output of approximately 1300 W, corresponding to about 59% of the installed capacity (2200 Wp), which reflects the system performance ratio under real operating conditions rather than the intrinsic efficiency of the PV modules. This study contributes to the selection of appropriate components that significantly improve the efficiency, reliability, and operational performance of the system. In conclusion, the SMART-based DSS effectively identifies the optimal components for a 2200 Wp off-grid solar power system, providing a practical and robust solution for electric vehicle charging under varying environmental conditions while ensuring improved efficiency, reliability, and system lifetime.

1. Introduction

A green campus is a term used to describe higher education institutions that have implemented green initiatives. Some important principles of a green campus include buildings, the environment, energy conservation, transportation, and so on (Fachrudin & Fachrudin, 2021). Among these aspects, energy management, particularly the adoption of renewable energy technologies, plays a critical role in reducing greenhouse gas emissions and supporting campus sustainability targets. Polman Bandung is one of the higher education institutions striving to become a green campus. However, previous studies indicate that implementing green campus strategies is often constrained by limited strategic planning, policy gaps, and uneven integration of sustainability indicators, particularly in the energy sector (Działek et al., 2025; Herzanita et al., 2024). Therefore, practical, technically grounded solutions are required, especially for optimizing renewable energy systems at the implementation level. Green campus strategies are hindered by regulatory barriers, financial constraints, and difficulties in shifting stakeholder behavior to mitigate emissions (Barnett-Itzhaki et al., 2025).

Solutions for realizing a green campus include the implementation of smart grids for autonomous energy management, wastewater reuse systems, and comprehensive master plans engaging stakeholders to develop green infrastructure from Hindayanti et al. (2024); Putri et al. (2024), Additional strategies involve IoT for real-time energy monitoring, digital twins for campus simulations, and machine learning for consumption predictions to minimize emissions from Viera et al. (2025), Policy leadership, sustainability education, green technologies, and cultural awareness campaigns among students are emphasized to disseminate sustainable development practices from Pereira et al. (2021), Campus living labs foster transdisciplinary collaboration for testing real-time sustainable practices to address social challenges (Herth et al., 2025). Rooftop solar PV on campus buildings emerges as a cost-effective strategy to slash GHG emissions, support educational initiatives, and enhance institutional reputation, with financial viability confirmed via consumption modeling from Seng & Sasso (2023), and Optimization via Neural Networks and Genetic Algorithms enables solar-powered multi-generation systems to deliver electricity, heat, and cooling for university buildings efficiently (Assareh et al., 2025).

One strategic approach to support green campus initiatives is the use of solar photovoltaic (PV) systems. Rooftop PV systems have been widely recognized as cost-effective solutions for reducing emissions and enhancing energy independence in campus environments (Seng & Sasso, 2023). In Polman Bandung, the development of a 2,200-watt solar power plant (PLTS) aims to support the electric vehicle infrastructure, also being developed by Polman Bandung. A solar power plant (PLTS) system is designed to convert sunlight into electrical energy through various systematic processes. Four essential components are required for optimal operation of a solar power plant (PLTS): solar panels, a solar charge controller, a battery, and an inverter. The performance and reliability of the system are highly dependent on the appropriate selection of these components, which must consider multiple criteria, including efficiency, compatibility, lifetime, and cost. However, the selection process is complex due to the availability of various component alternatives and the need to balance multiple technical and economic factors.

Previous studies on solar PV systems have primarily focused on technical optimization, such as efficiency improvement, system modeling, and energy output maximization, including the use of advanced methods such as neural networks, genetic algorithms, and solar tracking systems (Assareh et al., 2025; Kulaksız & Akkaya, 2012; Praveen & Menaka, 2024; Yang & Xiao, 2023). However, limited studies address the decision-making process for selecting optimal system components using structured multi-criteria approaches. Several decision-making methods, such as AHP, TOPSIS, and Fuzzy MCDM, have been widely applied in energy system analysis. Nevertheless, these methods often involve greater computational complexity, stricter consistency ratio requirements, or fuzzy parameter assumptions, which may reduce their practicality in real-world implementation.

This study addresses this gap by applying the Simple Multi-Attribute Rating Technique (SMART) as a Decision Support System (DSS) to select optimal components for an off-grid PLTS. Compared to other MCDM methods, SMART offers a simpler, more transparent weighting and scoring mechanism while maintaining robustness in multi-criteria evaluation. The novelty of this research lies in integrating SMART into a practical component-selection framework for a small-scale (2200 Wp) off-grid PV system specifically designed for electric vehicle charging infrastructure in a green campus context. Additionally, this study provides a quantitative comparison of component alternatives based on multiple criteria, a comparison that has not been explicitly addressed in previous PV optimization studies.

Based on the description above, a study was conducted to explore the application of the SMART method for selecting off-grid PLTS components at Polman Bandung, with a capacity of 2200 Wp, to support the transition towards a more sustainable and efficient green campus.

2. Method

Decision-making in selecting power generation technology is a complex process because it involves various technical, economic, social, environmental, and overall sustainability aspects (Parvaneh & Hammad, 2024). Therefore, decisions cannot be based solely on financial analysis, but need to be supported by a Multi-Criteria Decision Making (MCDM) approach that is able to accommodate various interrelated criteria (Sahoo & Goswami, 2023). One MCDM method that suits these needs is the Simple Multi-Attribute Rating Technique (SMART), because it has the characteristics of being simple, flexible, and considering the preferences of decision makers through criteria weighting (Valiris et al., 2005). This method uses an additive linear model that allows for the evaluation of alternatives based on quantitative and qualitative criteria, making it relevant in determining the optimal combination of main components in a 2200 WP Solar Power Plant (PLTS) system to support the Electric Vehicle Charging Station in Polman Bandung. As seen in Eq. (1), the model applied in SMART.

$$U(a_i) = \sum_{i=1}^{m} W_j u_j(a_i), \quad i = 1,2,\dots,m \tag{1}$$

Where:

j = criterion index , $j = 1, \dots, m$

i = alternative index, $i = 1, .., n$

m = number of criteria

n = number of alternatives

Wj = fixed weight assigned to criterion j

a_i = decision variance (alternative) i

$u_j(a_i)$ = evaluation of alternative a_i against criterion j

$U(a_i)$ = final value of alternative i

The sequence of using the SMART method based on the above function is as follows in Risawandi & Rahim (2016): (i) determine the number of criteria to be used in the decision-making process (ii) each criterion is given a weight using a scale of 1-100, where the weight reflects the level of urgency and priority of each criterion (iii) normalize the weight by dividing the weight of each criterion by the total weight, so as to obtain a uniform proportional value (iv) each alternative is given a parameter value according to the specified criteria (v) the parameter value is then converted into a utility value so that it can be compared objectively. The utility calculation is done using the Eq. (2) and Eq. (3).

$$u_i(a_j) = \frac{C_{out} - C_{min}}{C_{max} - C_{min}} \tag{2}$$

Where $u_i(a_j)$ is the utility value of criterion i against alternative j. The C_{max} value indicates the maximum value of a criterion. C_{min} is the minimum value of the criterion, and C_{out} is the output value for a particular criterion?

$$C_{out} = u_i(a_j); 1 = 0; 2 = 0{,}5; 3 = 1 \tag{3}$$

Determine the final value of each criterion by subtracting the value obtained from the results of normalizing the initial data with the normalized criterion weight.

2.1. Component Selection Flowchart

As seen in Fig. 1, shown shows the main stages in the process of selecting optimal components for a 2200 WP PLTS for an Electric Vehicle Charging station in Polman Bandung.

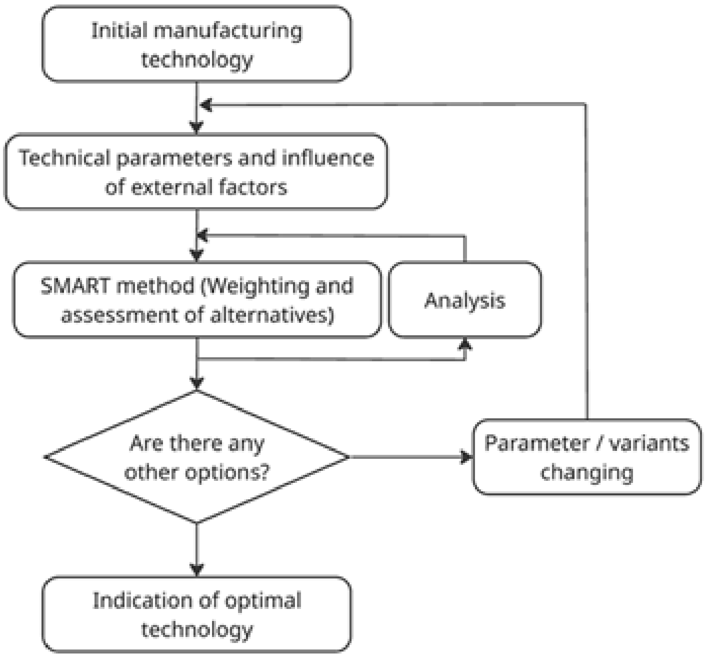

Fig. 1. Decision-making process using the SMART method

The initial step in implementing the SMART method is identifying technical parameters, including identifying problems and the influence of external factors on decision-making, as a crucial step before determining alternatives (Bhatia & Williams, 2023). Problem identification is carried out to determine energy needs and generating technology that aligns with the SPKLU in Polman, Bandung. Thus, problem identification is a key step in further evaluating technological alternatives. The next stage is technical data analysis. At this stage, the technical parameters of the solar power plant (PLTS) technology alternatives are studied in depth to ensure the technical feasibility of each option. Valid and measurable technical data is crucial to support the multi-criteria decision-making process, because without a strong technical basis, evaluation results can be biased or inconsistent with actual conditions (Wang et al., 2009).

The next stage is applying the SMART method to weight and assess alternatives. At this stage, each predetermined criterion is assigned a weight according to its level of importance. The solar power plant (PLTS) technology alternatives are then evaluated based on these criteria (Leon-Becerra et al., 2023; Purnama et al., 2025). The SMART method combines qualitative and quantitative criteria in a linear additive model to obtain the total utility value for each alternative (Taherdoost & Mohebi, 2024). After weighting and assessment, the next stage is the evaluation of other options. This stage is necessary to ensure that the decision is not limited to a single choice. This evaluation helps avoid bias towards a single option and provides a strong basis for decision-making (Pohekar & Ramachandran, 2004). From the evaluation and comparison of various alternatives, the solar power plant technology option was obtained with the highest utility value based on the SMART method. This technology is considered the most appropriate solution because it meets technical, economic, and sustainable criteria (Romadin et al., 2021). The optimal technology indication also serves as the basis for further implementation planning, both on a research scale and in the development of real projects. This decision ensures that the technology choice is not only technically feasible but also aligned with future needs such as energy efficiency and carbon emission reduction (Streimikiene et al., 2012).

2.2. Calculation of PLTS Component Specification Requirements

The solar power plant currently under development on the Polman Bandung campus will serve as the energy source for the Polman Bandung electric vehicle charging station. The specifications for each component are calculated based on the primary solar panel requirement of 2200 watt-peak (Wp). For the system to function effectively, the main components must complement each other, from the solar panels, SCC, batteries, and inverters to match the current and voltage output of the solar panels.

The capacity of a solar power plant (PLTS) must be determined based on the daily energy needs of an electric vehicle to meet the power requirement of 960 Watt-hours (Wh). The efficiency of the PLTS system, which generally ranges from 11 to 22%, must also be taken into account. Assuming an efficiency of 16%, the daily energy requirement will increase to 6,000 Wh. Furthermore, the number of hours of effective sunlight per day is assumed to be 5 hours in areas with good sunlight. Therefore, the required PLTS capacity can be calculated by dividing the daily energy requirement by the number of hours of effective sunlight, resulting in approximately 1,200 Wp. The PLTS designed on the Polman Bandung campus has a capacity of 2,200 Wp, although previous calculations indicated the required capacity was only 1,200 Wp. This larger solar power plant capacity was chosen to address several potential issues. First, the solar power system's efficiency may not reach 100% due to energy losses during the conversion and transmission process, which can reach 20-30%. Second, it ensures optimal battery charging to extend battery life (Madani et al., 2025; Ria & Dini, 2024). Third, it provides long-term economic benefits by reducing the need for additional capacity in the future (Nurfaidah et al., 2019; Oktavianti et al., 2019).

Calculating the specifications required for a Solar Charge Controller (SCC) for a 2200 Wp Solar Power Plant (PLTS) system aims to ensure the device meets system requirements and operates optimally. The primary function of the SCC is to regulate the current and voltage from the solar panel to the battery, ensuring a safe and efficient charging process (Kumar et al., 2025; Schwertner et al., 2025). The maximum current the SCC must handle is determined using Eq. (4) and Eq. (5).

$$I_{max} = \frac{P_{total}}{V_{system}} \tag{4}$$

Where P_{total}l is the total capacity of the solar panel, which is 2200 Wp, and System is the nominal system voltage, which is 48V. So, the maximum system current value obtained is shown in Eq. (5).

$$I_{max} = \frac{2200\ Wp}{48\ V} = 45{,}83\ A \tag{5}$$

To ensure system safety and reliability, a margin of approximately 25% is added to the current capacity that the SSC must handle so that the recommended minimum current is calculated using Eq. (6).

$$I_{controller} = I_{max} \times (1 + margin) \tag{6}$$

$$I_{controller} = 45{,}83 \times (1 + 0.25)$$
$$I_{controller} = 57.28\ A$$

The battery is a vital component in a solar power plant (PLTS), storing the electrical energy generated by the solar panels for use in the absence of sunlight, such as at night or during inclement weather. Therefore, before determining the PLTS specifications, it is important to first consider the battery specifications and energy requirements of the Polman electric vehicle. This ensures that the PLTS system can meet energy needs efficiently and effectively. Table 1 describes the battery specifications of the electric vehicle currently being developed by Polman Bandung. Referring to the data in Table 1, the daily energy requirement of the electric vehicle is 960 Watt-hours (Wh).

Table 1. Battery Specifications Used in Electric Vehicles

Specifications	Value
Battery Type	LiFePO4
Capacity	20 Ah
Minimum Voltage	3.2 V
Total Voltage	48 V

Determining the appropriate battery capacity requires several parameters, including the system voltage. Daily power requirements are calculated based on the total energy consumption by the load in one day. Referring to the previous calculation of daily power consumption of 6000 Wh, battery capacity can be calculated using Eq. (7).

$$C_{batttery} = \frac{E_{daily}}{V_{system} \times DOD \times \eta} \tag{7}$$

With a system voltage of 48 V, DoD = 0.5 and efficiency of 90%, the minimum battery capacity required is 278 Ah at a voltage of 48 V. An inverter is an important component in a solar power system that converts direct current (DC) generated by solar panels and stored in batteries into alternating current (AC) (Saikia et al., 2024). The inverter's working capacity, which is directly related to the electrical load, is measured in watts. The maximum load received must be smaller than the inverter capacity (Maka & Chaudhary, 2024). Inverter selection must consider two main things, namely power capacity and input voltage.

The inverter has the ability to handle peak power and continuous power. Peak power is the maximum power capacity that can be produced by the inverter in a short time. Meanwhile, continuous power is the power capacity that can be produced by the inverter continuously for a long time without overheating or damage. Therefore, to determine the inverter specifications, it is necessary to first identify the peak power and continuous power that the inverter will handle. The inverter voltage must also match the output voltage of the battery used.

2.3. Determining the types of main components in an off-grid solar power system

In designing a 2,200 Wp off-grid solar power system in Polman, Bandung, selecting key components is a crucial step because each device has its own unique characteristics, advantages, and limitations. Here are some components that will be used as alternatives for the Polman Bandung solar power plant, as shown in the following Table 2.

Table 2. Types of main components in the Polman Bandung off-grid PLTS system

Solar Panels	Polycrystalline Monocrystalline
Solar Charge Controller	Pulse Width Modulation Maximum Power Tracking Point
Battery	Valve Regulated Lead Acid Lithium Iron Phosphate
Inverter	Pure Sine Wave Modified Sine Wave

2.4. Implementation of the SMART method

The decision support system used in the process of selecting the main components of the solar power plant is the Simple Multi-Attribute Rating Technique (SMART) method. This method was chosen because it is simple to use and relevant to the case to be solved. This method was first developed by (Edwards, 1977). The SMART method is a technique used in decision-making systems to assess different alternatives based on a set of criteria attributes. The SMART method is useful when faced with several options to be evaluated, and each option has a number of relevant attributes.

2.4.1 Determination of Criteria

Criteria determination is carried out to ensure that the designed off-grid solar power system can achieve optimal performance according to its design objectives. In this study, four main criteria were identified as the most influential in the component selection process: (1) Function, (2) Compatibility (3) Lifetime, (4) Price. Functionality (C1) was chosen because it directly relates to a component's ability to effectively perform its role within the system. Compatibility (C2) was considered to ensure each component can be properly integrated without causing operational disruptions. Lifetime was chosen as a criterion because it relates to long-term system reliability, while price (C4) remains a critical factor in maintaining cost efficiency and project sustainability.

2.4.2 Determination of Criteria Weight

Once the criteria are determined, the next step is to assign weights to each criterion to reflect its level of importance. This weighting is done by considering the priority scale based on the research objectives. The highest weight is given to function (0.35) because this aspect is the main determinant of the system's success in generating energy. Compatibility is given a weight of 0.30 because the integration between components greatly influences system stability. Lifetime is given a weight of 0.20 because component durability will impact long-term maintenance and replacement costs. And finally, price is given a weight of 0.15 as a form of economic efficiency consideration. The results of the normalization of the criteria weights can be seen in Table 3, which will be used as the basis for the next stage of analysis and decision-making.

Table 3. Weight of criteria for each component

Criteria	Weight	Normalized Weight Values (wj)
Function (C1)	35	35/100 = 0,35
Compatibility (C2)	30	30/100 = 0,30
Lifetime (C3)	20	20/100 = 0,20
Price (C4)	15	15/100 = 0,15
Total	100	

2.4.3. Determination of Sub-Criteria Values

The determination of sub-criteria values is carried out to provide a more detailed assessment of each of the previously established main criteria. These sub-criteria are subjective because they consider the specific needs of the off-grid solar power system in Polman, but they still reflect actual technical conditions in the field. By determining sub-criteria values, each alternative component can be evaluated more accurately based on its characteristics. Each criterion is assigned a value according to its sub-criteria, as shown in the following Table 4.

Table 4. Solar panel sub-criteria values

Criteria	Description	Sub-criteria values
Function	Compare tool functions.	High functional capability = 60, Low functional capability = 40
Compatibility	Maximum performance when combined with other components	Maximum = 70 Below maximum = 30 Not maximum = 0
Lifetime	Component lifetime	High lifetime, value = 65 Low lifetime, value = 35
Price	Price comparison (try to compare similar specifications and brands).	1.5 – 2 million, value = 55 2.1 – 2.5 million, value = 35 More than 2.5 million = 15

Table 5, Table 6, and Table 7 present the sub-criteria values used to evaluate solar charge controllers (SCC), batteries, and inverters, respectively, based on function, compatibility, lifetime, and price. Each criterion is assigned a quantitative score to reflect performance levels, enabling consistent and objective comparison of alternatives within the SMART framework. The use of uniform evaluation criteria across components ensures methodological consistency, while the defined scoring ranges facilitate systematic assessment based on both technical performance and economic considerations.

Table 5. SCC sub-criteria values

Criteria	Description	Value
Function	Compare tool functions.	High functional capability = 60, Low functional capability = 40
Compatibility	Maximum performance when combined with other components	Maximum = 70 Below maximum = 30 Not maximum = 0
Lifetime	Component lifetime	High lifetime value = 65 Low lifetime value = 35
Price	Price comparison (try to compare similar specifications and brands).	Rp. 350,000 – Rp. 1,000,000 = 55 Rp. 1,000,000 – Rp. 1,500,000 = 35 More than Rp. 1,500,000 = 15

Table 6. Battery sub-criteria values

Criteria	Description	Value
Function	Compare tool functions.	High functional capability = 60, Low functional capability = 40
Compatibility	Maximum performance when combined with other components	Maximum = 70 Below maximum = 30 Not maximum = 0
Lifetime	Component lifetime	*High lifetime value = 65* *Low lifetime value = 35*
Price	Price comparison (try to compare similar specifications and brands).	3 million – 5 million value = 55 5 million – 8 million value = 35 More than 8 million = 15

Table 7. Inverter sub-criteria values

Criteria	Description	Value
Function	Compare tool functions.	High functional capability = 60, Low functional capability = 40
Compatibility	Maximum performance when combined with other components	Maximum = 70 Below maximum = 30 Not maximum = 0
Lifetime	Component lifetime	High lifetime value = 65 Low lifetime value = 35
Price	Price comparison (try to compare similar specifications and brands).	< 1 million – 2 million = 55 2.1 million – 2.5 million = 35 More than 2.5 million = 15

The sub-criteria values for function, compatibility, lifetime, and price across the Solar panel, SCC, Battery, and Inverter categories are based on established industry standards, including IEC 61215 and ISO standards. The functionality values (high = 60, low = 40) align with performance benchmarks from IEC 61215, which defines testing for solar module performance under various environmental conditions. Compatibility values (maximum = 70, below maximum = 30, not maximum = 0) reflect integration tests as per ISO 9001 and IEC 61730 for system compatibility.

The lifetime values (high = 65, low = 35) are derived from IEC 61215 degradation tests, such as thermal cycling and damp heat, which simulate long-term operational life. The price sub-criteria (e.g., Rp 350,000 – Rp 1,000,000 = 55) are informed by market value comparisons in line with ISO 9000 pricing standards. For solar panels, high functional capability is valued at 60, and high lifetime at 65, consistent with industry expectations. These criteria ensure the evaluation process is objective, grounded in reliable standards, and aligned with both empirical data and market trends.

2.5. Comparison of Utility Value and Final Value of Components

The next step is to determine the utility value of each alternative against the established criteria. This process aims to determine the extent to which each alternative component meets the criteria of function, compatibility, lifetime, and price. The assessment is based on the relative performance evaluation of each alternative primary solar power plant component. The utility value is calculated using Eq. (2). The score is then multiplied by the normalized weight of each criterion, as shown in Eq. (1). The utility assessment results for each primary component during the criteria evaluation stage are shown in Table 8, which includes the relationship between each alternative and the criteria being assessed. The total utility value and ranking of each alternative are then presented in Table 9. To ensure the robustness of the decision-making model, a sensitivity analysis was conducted by varying the criteria weights within a predefined range (±10%) to evaluate the stability of the resulting rankings in Table 10.

Table 8. Utility value of each component at the criteria evaluation stage

Components	Function Criteria		Compatibility Criteria		Lifetime Criteria		Price Criteria	
	Criteria-Alternative	Results						
Solar Panels	C1-A1	1	C2-A1	1	C3-A1	1	C4-A1	1
	C1-A2	0	C2-A2	1	C3-A2	0	C4-A2	1
SSC	C1-A3	1	C2-A3	1	C3-A3	1	C4-A3	0
	C1-A4	0	C2-A4	1	C3-A4	1	C4-A4	1
Batteries	C1-A5	1	C2-A5	1	C3-A5	1	C4-A5	1
	C1-A6	0	C2-A6	1	C3-A6	0	C4-A6	1
Inverters	C1-A7	1	C2-A7	1	C3-A7	1	C4-A7	1
	C1-A8	0	C2-A8	0	C3-A8	1	C4-A8	1

Table 9. The final value of each component

Components	Alternatives	Function Criteria	Compatibility Criteria	Lifetime Criteria	Price Criteria	Total	Ranking
Solar Panels	A1	1	1	1	1	1	1
	A2	0	1	0	1	0,45	2
SSC	A3	1	1	1	0	0,85	1
	A4	0	1	1	1	0,65	2
Batteries	A5	1	1	1	1	1	1
	A6	0	1	0	1	0,45	2
Inverters	A7	1	1	1	1	1	1
	A8	0	0	1	1	0,35	2

Table 10. Sensitivity table analysis

Scenario	Solar Panels	SSC	Batteries	Inverters	Ranking Change
Solar Panels	A1 (1) > A2 (0,45)	A3 (0,85) > A4 (0,65)	A5 (1) > A6 (0,45)	A7 (1) > A8 (0,35)	-
+10%	A1 > A2	A3 > A4	A5 > A6	A7 > A8	No change
-10%	A1 > A2	A3 > A4	A5 > A6	A7 > A8	No change

3. Results and Discussion

Based on the research results using the SMART method that has been used on all alternative main components in the off-grid PLTS system, the total utility value for each component is obtained as shown in Table 11. This utility value describes the level of suitability of each alternative to the predetermined criteria, namely function, compatibility, service life, and price.

Table 11. Recommendations for the best components based on utility evaluation results

Solar Power Plant Components	Best Alternative	Total Utility Value	Description
Solar Panels	Monocrystalline (A1)	1,00	High efficiency and long service life
Solar Charge Controller	MPPT(A3)	0,85	High charging efficiency and good compatibility
Batteries	Lithium Iron Phosphate Battery (LiFePO4) (A5)	1,00	Long service life and competitive price
Inverters	Pure Sine Wave (A7)	1,00	Smooth output waveform and high efficiency

The selection of monocrystalline solar panels is consistent with previous studies in Gunawan et al. (2025), which reported higher efficiency compared to polycrystalline panels. Similarly, the use of MPPT charge controllers aligns with findings by Dalle et al. (2024), where MPPT systems significantly improved energy harvesting under variable irradiance conditions.

3.1. Electrical circuit diagram testing

As seen in Fig. 2 below shows the electrical design of an off-grid solar power system designed to supply energy to an electric vehicle charging station. The current and voltage output from the solar panel circuit with a load of 63.2V and 34.8A will be controlled by an SCC MPPT as a charging source for the storage battery. Before connecting to the battery, a 63A DC MCB must be installed as a circuit breaker and safety device if the charging current exceeds 63A. However, the MPPT used can only handle currents up to 60A, while the maximum current generated by the solar panel with a load of only 34.8A. This means that the MPPT and MCB can handle the current generated by the solar panel. The electrical circuit for charging the solar panel to the battery is controlled by the SCC MPPT. Furthermore, to be used as a charging source for the Polman electric car, an inverter is needed to convert DC current to AC current because the Polman electric car battery charger requires AC input.

As seen in Fig. 2, the capacity of the Polman 20Ah 48V electric car battery, based on the electric power formula, means this battery has a power of 960 Watts. Therefore, the inverter must be able to handle the power from the Polman electric car battery. The inverter used is a Pure Sine Wave type because only this inverter produces a sine wave that almost perfectly resembles an AC current sine wave. This tool has a Peak Power specification of 3000 Watts and a Continuous Power of 1500 Watts. The output of the inverter is an AC current of 220V. To extend its lifespan, the load power should not exceed the continuous power limit of 1500 watts. The Polman electric car battery has a power of 960 watts, indicating that the inverter can adequately handle the power from this battery. However, it is recommended to install a 6A AC MCB on one of the output lines for safety and protection. So, the maximum power output that can be delivered by the 6A AC MCB is only 1320 Watts.

In addition, the coordination between the inverter capacity and the protective device ensures that the overall system operates within safe electrical limits while maintaining efficiency during operation. Although the inverter is capable of delivering up to 1500 W continuously, the installation of a 6A AC MCB effectively limits the output to 1320 W, providing an additional safety margin against overload and potential short circuits. This configuration not only protects the inverter and connected loads but also enhances system reliability during the electric vehicle charging process. Therefore, the integration of properly rated protection devices alongside the inverter plays a critical role in ensuring stable, safe, and sustainable operation of the off-grid solar charging system.

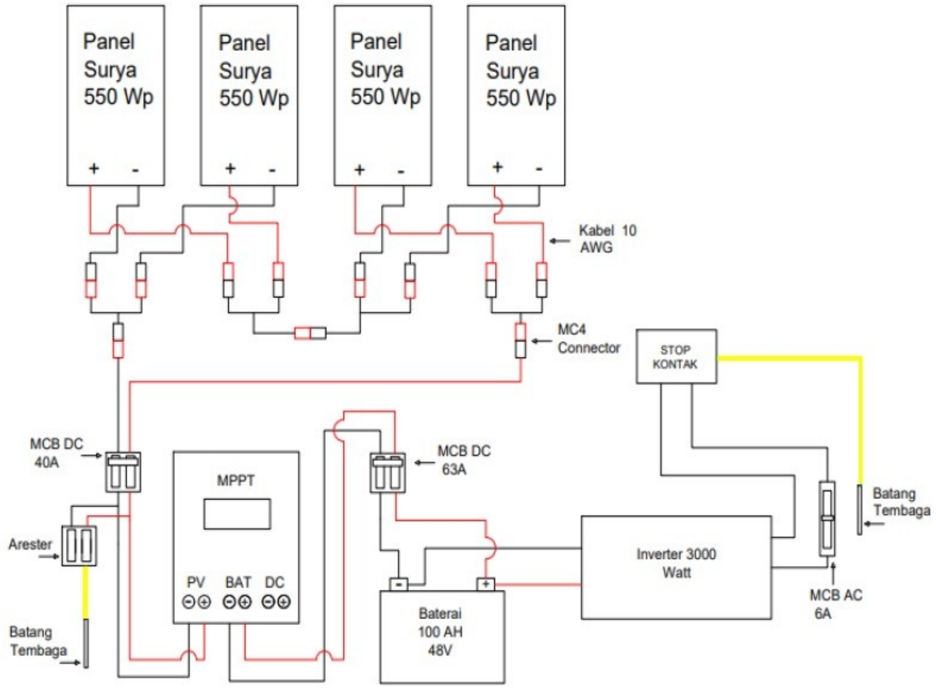

Fig. 2. Electrical diagram of 2200 WP PLTS

3.2 Solar panel testing

A solar panel is considered functional if it can generate voltage when exposed to sunlight. Voltage testing is performed using a multimeter. On June 27, 2024, at 12:04 a.m. WIB, the voltage of each solar panel was verified. The image shows that all solar panels are functional, as they can generate a voltage of 32 V in Fig. 3. The Open Circuit Voltage (VOC) listed in the panel specifications is 37.9 V, but due to various factors such less than optimal light intensity, the solar panels can only generate a VOC of 32 V.

Fig. 3. Solar panel verification process

3.3. Battery testing

Once the battery is activated, four SOC indicator lights will be active, indicating the battery's capacity. Each indicator light indicates 25% of the battery's capacity. Also, ensure the ALM indicator light is off, indicating the battery is in normal condition and functioning. The RUN indicator light will be active (flashing) when the battery is being used by a specific load or is in a discharge state.

$$DoD(\%) = \frac{E_{used}}{E_{total}} x\ 100\% \tag{7}$$

The battery is equipped with a factory-installed Battery Management System (BMS). The BMS sets the upper voltage limit at 54.75 V (when the battery is fully charged), while the lower voltage limit is 40 V (when the BMS protects the battery's output). The BMS regulates the battery's depth of discharge (DOD) at 73% in Fig. 4 and Eq. (7).

Fig. 4. Battery verification process

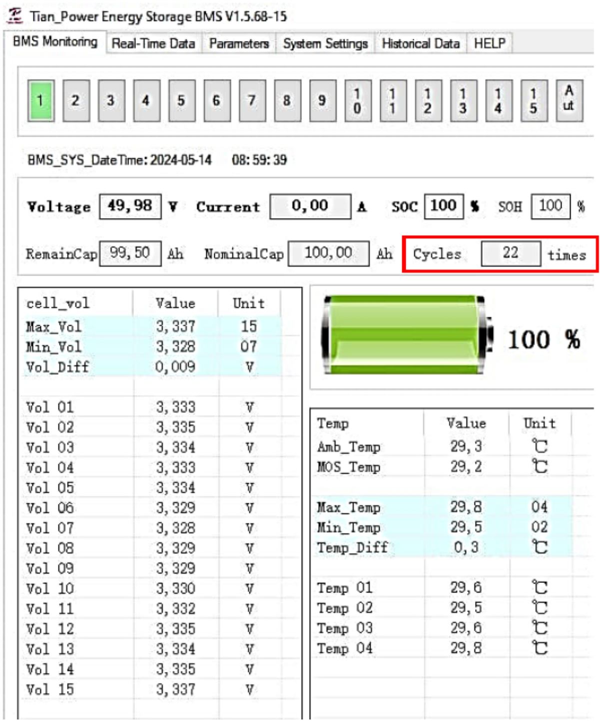

Fig 5. Battery testing process using Tian Power Energy software

Fig. 5 shows that the battery consists of 15 cells, each with an average voltage of 3.3V. The nominal voltage is 49.98V. Testing was conducted by the seller on May 14, 2024. Table 12 presents the measured PV output power over a 5-hour observation period under varying weather and shading conditions. The results indicate significant fluctuations in output, with higher power generated during bright conditions and a decrease observed during cloudy or shaded periods.

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Table 12. Data on the results of measuring the output power (Pout) of solar panels

Date	Time	PV Output (Watts)	Description
Tuesday, 16/07/2024	09:10 AM	194,9	Bright, tree-shaded
	09:25 AM	300,6	Bright, tree-shaded
	09:40 AM	710,4	Bright
	09:55 AM	1.100	Bright
	10:10 AM	1.200	Bright
	10:25 AM	1.200	Bright
	10:40 AM	1.300	Bright
	10:55 AM	1.300	Bright
	11:10 AM	1.300	Bright
	11:25 AM	1.000	Bright
	11:40 AM	1.300	Bright
	11:55 AM	1.300	Bright
	12:10 PM	333,1	Cloudy
	12:25 PM	1.300	Bright
	12:40 PM	1.200	Bright
	12:55 PM	1.300	Bright
	1:10 PM	1.200	Bright
	1:25 PM	232,9	Bright
	1:40 PM	37,3	Bright, tree-shaded
	1:55 PM	18,4	Bright, tree-shaded
	2:10 PM	9,5	Cloudy, tree shading
Total = 5 hours		Average = 849,4	

Table 13. Average data on power output (pout) and efficiency of solar panels

Date	Time	PV Output (Watts)	Efficiency (%)
Tuesday, 16/07/2024	09:10 – 10:10 AM	701,1	31,8
	10:10 – 11:10 AM	1260	57,2
	11:10 – 12:10 PM	1046	47,5
	12:10 – 13:10 PM	1066,6	48,4
	13:10 – 14:10 PM	299,6	13,6

The average PV output and corresponding efficiency across different time intervals are presented in Table 13, where peak performance is achieved during mid-day periods and efficiency is significantly reduced under lower irradiance conditions. The current (A) generated by the solar panel affects the battery charging speed. Based on the current output data in Table 14 the initial battery condition was 42.8V. On July 16, 2024, the battery was charged from 09:10 to 14:10 (five hours). The weather was predominantly sunny, but at 12:10, it was cloudy, and there was shade from 09:10 to 09:25 and 13:40 to 14:10. The table above explains bulk charging and boost charging. Bulk charging is a high-current charging process that increases the voltage to near the upper limit. Boost charging is a very low-current charging process to prevent the battery from overcharging. Boost charging activates when the battery voltage is close to full, in this case, at 54.4 V, which occurred between 1:25 PM and 2:10 PM. The charging process is carried out for five hours at an initial battery voltage of 40 V until fully charged at 54.75 V, or the battery requires a power input of 1296W. The average output current of the MPPT solar panels across different time intervals is presented in Table 15, where higher current values are achieved during mid-day periods and a significant decrease is observed in the afternoon.

Table 14. Battery charging data measured by SCC MPPT

Date	Time	Battery Input (A)	Battery Volts (V)	Description
Tuesday, 16/07/2024	09:10 AM	4,5	42,8	Bulk charging
	09:25 AM	6,7	44,8	Bulk charging
	09:40 AM	14,8	47,7	Bulk charging
	09:55 AM	23	48,5	Bulk charging
	10:10 AM	25,1	49,1	Bulk charging
	10:25 AM	25,9	49,5	Bulk charging
	10:40 AM	26,6	49,6	Bulk charging
	10:55 AM	26,4	49,6	Bulk charging
	11:10 AM	26,7	49,6	Bulk charging
	11:25 AM	20,8	49,5	Bulk charging
	11:40 AM	26,8	49,8	Bulk charging
	11:55 AM	27,6	50	Bulk charging
	12:10 PM	6,8	49	Bulk charging
	12:25 PM	26,7	50,1	Bulk charging
	12:40 PM	25,4	50,1	Bulk charging
	12:55 PM	26,6	50,3	Bulk charging
	1:10 PM	23,8	51	Bulk charging
	1:25 PM	4,2	54,4	Boost charging
	1:40 PM	0,6	54,4	Boost charging
	1:55 PM	0,3	54,4	Boost charging
	2:10 PM	0,1	54,4	Boost charging
Total = 5 hours		Average = 17,6		

Table 15. Average output current data on MPPT solar panels

Date	Time	Average current (A)
Tuesday, 16/07/2024	09:10 – 10:10 AM	14,8
	10:10 – 11:10 AM	26,1
	11:10 – 12:10 PM	21,7
	12:10 – 13:10 PM	21,8
	13:10 – 14:10 PM	5,8
Total time = 4 hours	Average Current = 18,04 A	

3.4. Inverter testing

As seen in Fig. 6, the inverter is considered to be functioning normally if, after the installation process with the battery, the green indicator light is activated, and the inverter will read the battery's DC voltage output and the inverter's AC voltage output. The red indicator will activate when the battery voltage reaches the lower limit (maximum usage), indicating that the battery is no longer usable and needs to be charged.

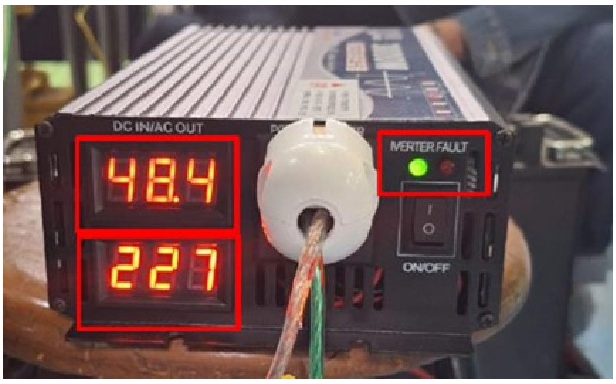

Fig. 6. Inverter verification process

3.5. MPPT solar controller testing

The MPPT will activate when powered by the battery. Once the MPPT is active, the first step is to check the work mode displayed on the MPPT display. As seen in Fig. 7, ensure the work mode code is not an alarm or error. In this experiment, the MPPT was in work mode 3.0, meaning the system was operating in night mode, with no charging.

Fig. 7. Solar charge controller verification process

3.6. Electric Car Battery Charging Testing in Polman

To supply the charging station's output from the inverter, a power outlet is installed to connect it to the Polman electric car battery charger. As seen in Fig. 8, the electric car charger has an input specification of 220V AC – 230V AC. This voltage meets the input requirements of the Polman electric car charger. The following test demonstrates that the inverter's output can charge the Polman electric car battery.

Fig. 8. Inverter voltage output

The experimental results further support the decision-making outcomes obtained using the SMART method. The selected configuration monocrystalline solar panels, MPPT charge controller, LiFePO4 batteries, and pure sine wave inverter demonstrates superior performance in terms of power output, charging stability, and system efficiency. As seen in Fig. 9, for instance, the PV output measurements show higher and more stable power generation under varying conditions, while the battery charging data indicate efficient energy storage and stable voltage characteristics. These findings are consistent with the criteria evaluation, where the selected components achieved the highest utility values. Therefore, the experimental validation confirms that the SMART-based selection approach is reliable and applicable for real-world implementation.

Fig. 9. Electric car battery charging trial in Polman

The results of this study are also consistent with previous research indicating that monocrystalline solar panels provide higher efficiency compared to other types (Gunawan et al., 2025). Similarly, the use of MPPT charge controllers has been widely reported to improve energy harvesting efficiency under varying irradiance conditions (Dalle et al., 2024). Compared to studies using optimization techniques such as neural networks or genetic algorithms (Assareh et al., 2025), the SMART-based approach offers a simpler yet effective decision-making framework for component selection. In terms of practical application, the proposed configuration is suitable for small-scale off-grid systems such as electric vehicle charging stations in campus environments. Furthermore, the decision-making framework can be adapted for larger-scale implementations by incorporating additional criteria such as scalability, maintenance cost, and grid integration, making it relevant for broader renewable energy deployment

4. Conclusion

In this study, an off-grid solar power plant (PLTS) system was designed using four main components: solar panels, a solar charge controller (SCC), a storage battery, and an inverter. The configuration of these components was selected to ensure a reliable supply of electricity in accordance with the planned load requirements. The analysis results indicate that functionality, compatibility, lifetime, and price are the most influential factors in determining the optimal off-grid PV system configuration. To support the decision-making process for selecting components for the 2200 Wp off-grid PV system, the Simple Multi-Attribute Rating Technique (SMART) method was used as a decision support system. The application of the SMART method provides a measurable approach to quantitatively assessing various criteria, resulting in the most appropriate component alternatives based on the highest utility value. This study contributes to the development of solar PV systems for electric vehicle charging applications by providing a practical and systematic decision-making framework for component selection using the SMART method, which can be applied in campus-scale and similar off-grid energy systems.

Furthermore, according to the utility evaluation result, the most optimal configuration for the solar power system includes Monocrystalline solar panels, MPPT charge controller Lithium Iron Phosphate ($LiFePO_4$) batteries, and a Pure Sine Wave inverter. The system is capable of producing an output of up to approximately 1300 W, corresponding to about 59% of the installed capacity, reflecting the system performance under real operating conditions rather than intrinsic panel efficiency. Experimental results also confirm that system performance is strongly influenced by solar irradiance, with optimal operation achieved under clear weather conditions. The test results also indicate that the performance of the off-grid PV system will be optimal when supported by clear weather conditions, which maximizes the intensity of solar radiation received by the solar panels. Under these conditions, the system is able to work efficiently and produce output power according to its design capacity. For future research, the proposed approach can be further developed by integrating SMART with other MCDM methods such as AHP or TOPSIS to enhance decision accuracy. In addition, future studies may incorporate additional parameters, including energy efficiency, life cycle cost, and sustainability analysis, to provide a more comprehensive evaluation of PV system performance.

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