Choosing The Right Photovoltaic Panel for Electric Vehicles: An Integrated Decision Support Model

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Abstract. In the current era, global carbon emissions are on the rise and to achieve environmental sustainability, greenhouse gas emissions must be reduced to net zero levels with greater reliance on renewable energy sources. Due to the increasing demand for sustainable transportation options, the integration of photovoltaic (PV) panels in electric vehicles (EVs) is considered a promising solution to boost energy efficiency and reduce greenhouse gas emissions. However, selecting the most suitable photovoltaic panel for EVs is a complex process that involves multiple criteria and considerations. This research article presents an integrated decision support model using the Best-Worst Method (BWM) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to assist in selecting the optimal module. The BWM is employed to compute the weights of eight identified criteria, reflecting the preferences and priorities of decision experts. Subsequently, the TOPSIS method is utilized to evaluate and rank a set of PV panel options based on their performance against the identified criteria. The results reveal that a mono-crystalline bulk silicon module is the best alternative followed by multi-silicon modules. This study proposes a structured decision approach for EV manufacturers to select the right PV panel, promoting energy-efficient transportation solutions.

1 Introduction

The urgent need for cleaner sources of energy to combat the environmental challenges posed by greenhouse emissions has led to the transition toward renewable sources from traditional ones [1]. This growing environmental concern has accelerated the need for electric vehicles (EVs) over vehicles that need fossil fuels for energy [2]. Solar energy being free and one of the best sources of renewable energy, presents a great application opportunity for EVs as sustainable products [3]. With the growing concerns and efforts toward a brighter future by utilizing the available natural resources, knowledge and technologies, it is believed that the United Nation's Sustainable Development Goals (UNSDGs) regarding climate actions, providing clean and modern energy, responsible consumption and production, and industry innovation (goals# 7, 9, 12, and 13) will be strengthened [4]. Hence, a shift from conventional to renewable energy sources is expected to bring a substantial change in transportation operations leading to lesser greenhouse gas emissions and global warming [5], [6].

Electric vehicles hold significant potential as a solution to revolutionize climate action goals by tapping into solar energy sustainably, owing to their unlimitedness. However, the greater adoption of EVs would depend on the distance they cover on a single charge, as developing charging stations equal to conventional fuel stations is another challenge. Photovoltaic panels are used to convert and store solar energy to provide vehicles with electric energy for their operations [3], [7]. There is a continuous reduction in cost and technological advancements that are supporting its wider adoption either offboard or onboard purposes [3], [8]. The need for onboard PV modules arises due to the intermittent levels of availability of these natural energy sources, which is because of the relative motion of the earth and the sun. As these onboard PV panels are supposed to be an efficient source of energy for EVs, there are certain limitations to it. Along with the intermittent availability of solar energy, the changing angle of incidence, space available for PV panels on these EVs, option of fixed or self-orienting panels are some of the roadblocks to its adoption [8]. Hence there is an urgent need for an investigation that helps in determining the optimum commercial PV technology that can overpower above mentioned barriers.

With the present research, the authors would attempt to provide a decision support model for selecting the optimum commercial onboard PV panel technology for EVs. The two promising multicriteria decision-making (MCDM) approaches would be integrated- the Best-Worst Method (BWM) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), for the PV panel technology selection, which en masse will help in effective and efficient navigation through the intricacies. As the selection criteria must accommodate qualitative aspects of the technology selection as well, this hybrid approach will be best suited to the current context. Overall, the chosen MCDM approach would used to increase the understanding of the complexities of adopting PV panel technology mounted on EVs for a better and cleaner climate efficiently.

2 Literature Background

Recent advancements in electronics and batteries have paved the way for a significant increase in the adoption of electric vehicles in the automotive industry. It is projected that by 2025, the share of EVs will increase by about 4.3 times compared to the current levels [9].

Harnessing solar energy for transportation offers numerous benefits, with PV panels exhibiting technological advancement and energy efficiency [10]. There have been several studies that have explored the applicability of the photovoltaic modules. In a study, the potential increase in electric vehicle mileage using commercially available solar energy technologies requiring minimal investment was assessed [7]. Another study compared three PV panels (N-PV, PCM-PV, and PCM-CPV) under different scenarios to test their effectiveness in charging L1 vehicles [11]. A study proposed an extended-range power supply system for electric vehicles using PV panels and batteries to overcome issues related to battery charging and discharging [12]. In other work, a foldable scissors mechanism was proposed for a portable, auxiliary photovoltaic power system for electric vehicles [13]. A study developed a model to estimate temperature effects on PV panels installed on cars under real meteorological conditions [14] while another study examined optimizing energy systems for electric vehicles using high-efficiency triple-junction solar cells (InGaP/InGaAs/Ge) [15]. Although Abdelhamid et al. [3] evaluated the PV modules using a QFD-AHP-based approach, the study addressed only the market data with no emphasis on the decision-maker's expertise. The present study aims to further the investigation by involving the judgments of the experts without comprising on the consistency issues encountered in AHP based approach.

2.1 Criteria for Selection of PV Panel

Selecting photovoltaic (PV) solar panels for charging electric vehicles requires careful consideration of several criteria to ensure optimal performance and compatibility. The criteria used for the selection are reported below.

2.1.1 Panel Efficiency (PE)

The solar panels installed and integrated with electric vehicles should maximize energy capture from the limited surface area. Higher efficiency panels can generate more electricity for charging the vehicle's battery. Hence, the panel efficiency is an important determinant of the suitable module.

2.1.2 Cost (COST)

When selecting photovoltaic (PV) panels for a solar energy system, cost is a critical factor that determines its feasibility and economic viability. The upfront cost of PV panels varies significantly, depending on the type of panel (monocrystalline, polycrystalline, thin-film, etc.). Evaluating the initial investment cost is crucial for budget planning and determining the practicality of the system.

2.1.3 Power Density (PD)

PV panels generate electrical power based on the amount of sunlight they receive. The power density of a panel measures how much electrical power can be produced per unit of surface area, and is typically expressed in watts per square meter (W/m^2). This value is determined under standard test conditions and indicates how efficient a panel is at converting sunlight into usable electricity.

2.1.4 Specific Weight (SW)

Specific weight refers to the output power generated per unit weight of the panel, measured usually in watts per kilogram (W/kg). It becomes a significant parameter to assess the feasibility of the PV panels.

2.1.5 Potential Material Hazards (PMH)

Assessing potential material hazards on account of the materials used in the panel becomes an important factor to assess the benefits of the PV panel installation. Minimizing or eliminating these hazardous materials such as lead, arsenic, and so forth is crucial to reduce environmental impact and hazards.

2.1.6 Material Availability (MA)

The commonly used materials include silicon for crystalline panels, cadmium, and tellurium for cadmium telluride (CdTe) panels, and copper, indium, gallium, and selenium for thin-film panels. It is crucial to consider whether these resources are abundant or scarce.

2.1.7 Durability (DUR)

Durability is a vital factor for photovoltaic panel selection as it directly impacts the longevity, reliability, and overall performance of a solar energy system. When considering durability, the key factors to assess include tolerance, material quality, and so forth.

2.1.8 Power Temperature Coefficient (PTC)

The power temperature coefficient quantifies how a PV panel's electrical output (power) changes with fluctuations in temperature. It is typically expressed as a percentage change in power per degree Celsius (°C) temperature change from a standard reference temperature.

2.2 Alternative PV Modules

The adoption of photovoltaic panels is largely affected by their costs, reliability, availability, and other lifetime-related constraints [16]. Since silicon is a widely available and well-researched element, it serves as the primary material in silicon-based solar cells. This study takes into account nine PV panel alternatives to be assessed using the eight criteria identified earlier. The alternative module choices include mono-crystalline silicon (Mono-Si); multi-crystalline silicon (multi-Si); amorphous silicon (am-Si); cadmium telluride (CdTe); copper indium gallium selenide (CIGS); double junction amorphous silicon (dj-a-Si); gallium arsenide (GaAs); organic photovoltaic (OPV); and dye-sensitized solar cells (DSSC).

3 Decision Approach

This section describes PV panel technology selection for electric vehicles by utilizing integrated MCDM techniques that are widely applied to providing decision support for crucial factors [17], [18]. Not only does BWM require fewer comparative statistics, but the results from BWM showcase significantly more consistency than other similar tools, such as the Analytical Hierarchy Process, which makes the approach more reliable [19].

The first step for solving this selection problem included the literature review and discussion with area experts to identify the selection criteria. The identified and approved criteria are then subjected to weight calculation by applying BWM. The resulting weights are further evaluated for alternative processes. Alternatives are evaluated by employing methods such as TOPSIS, VIKOR and PROMETHEE, out of which TOPSIS is preferred when a study examines several criteria and alternatives and data is quantitative [18]–[20]. TOPSIS ranks with greater clarity, rendering its implementation a logical choice. BWM-TOPIS has been widely employed in many research works that support the application of this robust hybrid MCDM technique in the present study.

3.1 BWM Approach

Step I. Decision factors are determined

Step II. The best and worst criteria are determined.

Step III. The relative importance of the best over others is established using a scale of 1-9. The best-to-others set is represented as $A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn})$ where a_{Bj} is the preference for best criterion over criterion j.

Step IV. Relative importance of all the criteria over the worst criterion is established using a scale of 1-9 and is written as $A_W = (a_{1W}, a_{2W}, \ldots, a_{nW})^T$ where a_{jW} is the preference of all factors j over the worst.

Step V: Determine weight of all the factors $(w_1, w_2, \ldots, w_n)$ using a LP model to minimize the maximum absolute differences $\{|w_B - a_{Bj}w_j|, |w_j - a_{jw}w_w|\}$.

$\min\max\{|w_B - a_{Bj}w_j|, |w_j - a_{jw}w_w|\}$

Subject to:

$\sum_j w_j = 1$

$w_j \geq 0, for\ all\ j$

The above model can be transformed into the following linear model:

$\min \varphi^L$

Subject to:

$|w_B - a_{Bj}w_j| \leq \varphi^L$, for all j

$|w_j - a_{jw}w_w| \leq \varphi^L$, for all j

$\sum_j w_j = 1$

$w_j \geq 0, for\ all\ j$

3.2 TOPSIS Approach

Step VI: The outcome of the final step of the BWM process is presented in a decision matrix, wherein decision criteria are listed in columns and alternatives are listed in rows.

Step VII: A normalized decision matrix is created

$$N_{ij} = \frac{X_{ij}}{\sqrt{\sum X_{ij\hat{2}}}}$$

Step VIII: A weighted normalized decision matrixv is created.

$$V_{ij} = W_j \times N_{ij}$$

Step IX: The positive ideal (Y_j^*) and negative ideal (V_j') solutions are obtained.

Y_j^* = set of all best values in each column

Y_j' = set of all worst values in each column

Step X: Separation measures are computed.

Separation from a positive ideal solution,

$D_i^* = \sqrt{\{\sum(Y_{ij} - Y_j^*)\hat{2}\}}$

from a negative ideal solution, $D_i' = \sqrt{\{\sum(Y_{ij} - Y_j')\hat{2}\}}$

Step XI: The relative closeness measure of all the alternatives is calculated.

$$CR = \frac{D_i'}{D_i' + D_i^*}$$

Step XII: The final ranks are determined in the decreasing order of the relative closeness.

4 Analysis

In the present study, the authors reached out to three domain experts specializing in the power and electronics sectors. They had an average of twenty years of experience and were asked to assess the best and worst criteria. Following this, they were requested to provide a pairwise comparison of the criteria with the previously identified best and worst criterion. Their responses were used to obtain the final weights of the criteria from the BWM steps detailed above, and given in Table 1.

Table 1. Weights computed from BWM

Criteria	**PE**	**COST**	**PD**	**SW**	**PMH**	**MA**	**DUR**	**PTC**
Weight	0.21	0.08	0.33	0.07	0.06	0.03	0.14	0.08

Based on the findings presented in Table 1, power density (PD) is the top priority factor with a relative importance of 33%, followed by panel efficiency (PE) and durability (DUR) with preferences of 21% and 14% respectively. On the other hand, experts gave the lowest preference score to expansion material availability, with only 3% weight.

During the next phase, the TOPSIS procedure is utilized to assess the PV panels based on the criteria and their weights, which were previously obtained by BWM. Five experts were contacted and requested to rate the alternatives based on the factors, using a scale of 1 to 5. The aggregated responses are normalized and depicted in Table 2.

Table 2. Normalized Matrix

	PE	**COST**	**PD**	**SW**	**PMH**	**MA**	**DUR**	**PTC**
Mono-Si	0.35	0.27	0.25	0.33	0.32	0.46	0.26	0.30
GaAs	0.30	0.38	0.38	0.43	0.35	0.24	0.30	0.29
OPV	0.35	0.29	0.40	0.22	0.37	0.24	0.30	0.34
Multi-Si	0.22	0.36	0.20	0.37	0.28	0.24	0.28	0.42
am-Si	0.39	0.21	0.38	0.39	0.37	0.31	0.41	0.29
CIGS	0.39	0.31	0.30	0.33	0.28	0.33	0.34	0.29
DSSC	0.30	0.44	0.40	0.32	0.34	0.46	0.34	0.38
DJ-a-Si	0.32	0.42	0.33	0.24	0.37	0.31	0.37	0.34

CdTe	0.34	0.25	0.30	0.32	0.30	0.33	0.37	0.32

The weighted normalized matrix is computed by multiplying the normalized matrix columns with respective criteria weights, as shown in Table 3.

Table 3. Weighted Normalized Matrix

	PE	**COST**	**PD**	**SW**	**PMH**	**MA**	**DUR**	**PTC**
Mono-Si	0.07	0.02	0.08	0.02	0.02	0.01	0.04	0.03
GaAs	0.06	0.03	0.13	0.03	0.02	0.01	0.04	0.02
OPV	0.07	0.02	0.13	0.02	0.02	0.01	0.04	0.03
Multi-Si	0.05	0.03	0.07	0.03	0.02	0.01	0.04	0.03
am-Si	0.08	0.02	0.13	0.03	0.02	0.01	0.06	0.02
CIGS	0.08	0.03	0.10	0.02	0.02	0.01	0.05	0.02
DSSC	0.06	0.04	0.13	0.02	0.02	0.01	0.05	0.03
DJ-a-Si	0.07	0.03	0.11	0.02	0.02	0.01	0.05	0.03
CdTe	0.07	0.02	0.10	0.02	0.02	0.01	0.05	0.03

Next, we computed the separation measures for all nine PV panel alternatives using the positive and negative ideal values explained in the Step X of the previous section. Afterward, we calculated the relative closeness using Step XI. Table 4 shows the separation measures, relative closeness for all the alternatives, and their ranks.

Table 4. Separation Measures, Relative Closeness and Alternatives' Ranks

Alternative	**D+**	**D-**	**Closeness**	**Rank**
Mono-Si	0.0332	0.0580	0.6364	1
GaAs	0.0647	0.0274	0.2972	8
OPV	0.0718	0.0294	0.2903	9
Multi-Si	0.0407	0.0695	0.6305	2
am-Si	0.0626	0.0432	0.4086	6
CIGS	0.0388	0.0509	0.5675	3
DSSC	0.0705	0.0300	0.2984	7
DJ-a-Si	0.0473	0.0397	0.4560	5
CdTe	0.0410	0.0440	0.5179	4

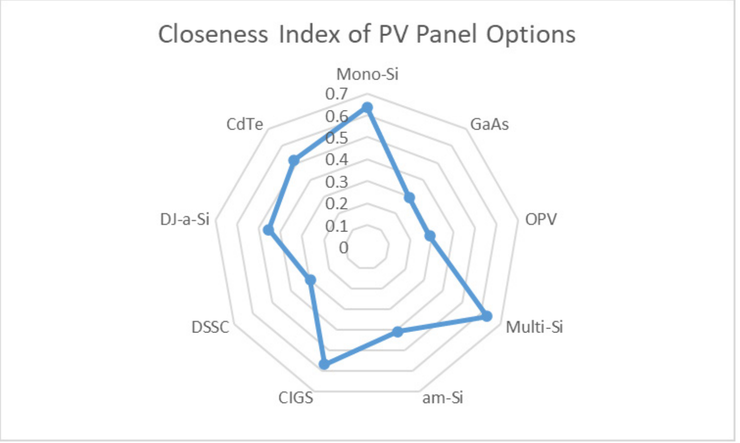

Fig.1. Relative closeness Indices of PV panels

Mono-crystalline silicon panels have been ranked as the top choice for integration into EVs as shown in Figure 1. This ranking suggests that experts consider mono-crystalline silicon panels to be the most suitable and effective option among the available PV technologies for powering electric vehicles. This preference is likely due to their high efficiency, power density, low costs, and widespread availability. Following mono-crystalline silicon, multi-crystalline silicon panels are ranked as the second-best alternative. Multi-crystalline silicon panels are known for their cost-effectiveness and reasonable efficiency. In contrast, OPV and GaAs panels are less favored, likely due to concerns about their efficiency, durability, or cost-effectiveness in the context of EVs.

5 Concluding Remarks

This study proposed a hybrid decision model based on BWM-TOPSIS for the selection of the most suitable photovoltaic (PV) panels for electric vehicles. The study considered eight criteria for the decision including panel efficiency, durability cost, material availability, and material hazards. Further, nine alternative PV panels were analyzed with the help of judgments received by a panel of domain experts. The results report that mono-crystalline silicon panels are the best alternatives, followed bymulti-crystalline and copper indium arsenide panels respectively. The study primarily contributes by putting forth an integrated decision support model to PV panel selection for EVs, considering multiple criteria. This may enables the policymakers to make informed decisions with due consideration of all the relevant decision factors, contributing to the sustainable and efficient integration of solar power into the rapidly evolving world of electric vehicles.

This study offers numerous prospects for future investigations in the domain. Future works may explore some more technologies that may increase the efficiency and the effectiveness of the currently available choices. Further, the complex interdependencies among the factors may also be analyzed in future research. Some statistical models and experimental designs may balso be worth developing in the domain to further expand the body of literature in the domain of EVs and PV panels..

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