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***Abstract*—This paper presents an overview of different commercial photovoltaic (PV) module options to power on-board electric vehicles (EVs). We propose the evaluation factors, constraints, and the decision-making criteria necessary to assess the suitability of this PV module for this application. The incorporation of quality function deployment (QFD) and the analytical hierarchy process (AHP) is the decision-making methodology used in this study. Our approach is innovative and robust in that the evaluation depends upon data collected from PV manufactures datasheets. Unlike traditional research, a hybrid AHP and QFD innovative decision-making methodology has been created, and current commercial PV market data for all pairwise comparisons are used to show that methodology. Using both cooled and uncooled PV modules, best, intermediate, and worst-case scenarios were used to estimate the driving ranges of lightweight EVs powered exclusively by bulk silicon PV modules. Results showed that the available daily driving ranges were between 25 and 60 km and that the CO_2 emissions were reduced between 3 and 6.5 kg, compared with internal combustion vehicles of a similar type. We found that mono-Si PV modules were most suited to power low-speed, lightweight, and aerodynamically efficient EVs.**

***Index Terms*—Analytic hierarchy process (AHP), electric vehicles (EVs), photovoltaic cells, quality function deployment (QFD), ranges, solar energy.**

I. Introduction

THE nonsustainable nature of fossil fuels and the increasing awareness about environmental pollution has resulted in the creation of vehicles that use alternative fuel sources such as electric vehicles (EVs), hybrid electric vehicles (HEVs), and plug-in hybrid electric vehicles (PHEVs). Photovoltaic (PV) technologies, in which solar energy is captured and converted to direct current electricity, have also been developed because of the availability of resources to create such technologies and because of the ubiquitous nature and zero cost of solar energy. The PV module, which is a packaged assembly of individual PV cells, can provide energy to the vehicle via either on-board or off-board methods. In off-board applications, PV is the source of energy for the charging station. In on-board applications, the PV modules are vehicle mounted or integrated either to assist in propulsion or to run a specific vehicle application [1]–[4]. There has been substantial interest in developing PV technologies for transportation because of the rapid evolution of these technologies in terms of increased efficiency and reduction in cost. The approaches vary in terms of the PV module type, specifications, and configuration of the system.

However, thus far, no research has been undertaken to determine the efficiency of decision-making methodologies to evaluate and select the optimum commercial PV module option of on-board EVs. In this study, we propose evaluation factors, constraints, and the decision-making criteria necessary to assess PV module's suitability for this application. We also present an overview of different commercial PV modules options. The proposed decision-making methodology is a combination of the quality function deployment (QFD) [5] and the analytical hierarchy process (AHP) [6]. This research reduces the subjectivity of these methods used with the inclusion of commercial PV market data for comparison and not from experts' experiences, as in traditional research. It is also innovative in that we add QFD as an input stage to correlate EV customers' needs with PV module capabilities. The remainder of this paper is organized as follows. In Section II, we provide a literature review, followed by our proposed methodology in Section III. In Section IV, we provide our range of results for an EV powered by PV modules and provide our conclusions in Section V.

II. Literature Review

Based upon a combination of qualitative and quantitative approaches, the AHP is a multicriteria decision-making (MCDM) method used to evaluate multiple and conflicting criteria. In the qualitative sense, it decomposes an unstructured problem into a systematic decision hierarchy. It then uses a quantitative ranking using numerical ranks and weights in which a pairwise comparison is employed to determine the local and the global priority weights and finally the overall ranking of the proposed alternatives. The AHP approach has been recently used to rank various renewable and nonrenewable electricity production technologies [7], for determining the best possible solar tracking mechanism [8], for selecting the most appropriate package of solar home system for rural electrification [9], for selecting the solar–thermal power plant investment projects [10], for determining the best sequence of switching [11], and for evaluating different power plants [12]. Recently, we used the AHP for selecting the best microcrack inspection technique for an automated PV production line [13].

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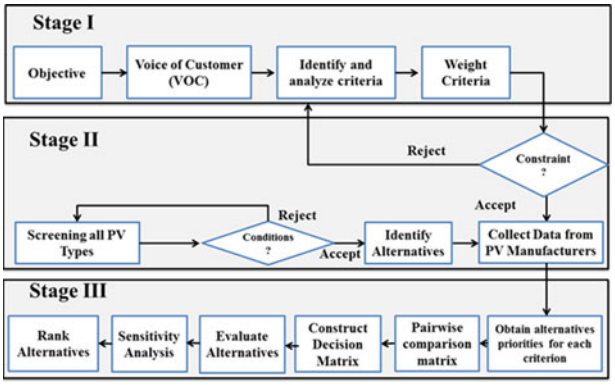

Fig. 1. Proposed methodology to select the optimum PV module option to power on-board EVs.

The QFD is a systematic method that the designer may use to develop a new product or service by learning about the needs of the customer, also known as the voice of the customer (VOC). The aim of QFD is to incorporate the VOC into the engineering characteristics of a specific product or a service. The planners can then prioritize each product or service attributes to set the levels necessary for achieving these characteristics. The QFD is used for various applications, and the combined AHP-QFD is applied to various situations [14], [15]. We implemented a QFD and AHP combination as a decision-making tool for material selection of automobile bodies [16] and to develop a knowledge-based system for designing an automotive production line [17].

There are many other MCDM models, all of which have their strengths, weaknesses, and areas of application, and none of which is truly superior [18]. The most common disadvantage between the MCDM tools is the subjectivity where the decision maker uses his/her experience to rank alternatives. Our proposed methodology minimizes the subjectivity and provides robust results. We chose the AHP decision making for these reasons: 1) Selecting the optimum PV module option for on-board EV is an MCDM problem with conflicting objectives; 2) the AHP is based on pairwise comparison and provides a robust decision tool if precise data are used; and 3) we must have the ability to incorporate QFD as an input stage so that weights are assigned according to EV customer's preference and reducing the subjectivity found in the traditional AHP method.

III. Methodology

The methodology used in this study is shown in Fig. 1. The objective is to select the optimum PV module options to power on-board EVs. We divide this approach in three main stages, as discussed in the following subsections.

A. Stage I: Quality Function Deployment

There are five key components in our QFD matrix (see Fig. 2). First, the "How" window is used to specify the engineering requirements. Here, we propose the decision-making criteria necessary to assess a PV module's suitability for commercial use for EV, which are the six PV functional requirements as specific

		Column #	1	2	3	4	5	6
Row #	Importance (α)	PV Modules Functional Requirement ("Hows") / EV Requirements ("Whats")	Power Density (W/m^2)	Specific weight (W/kg)	Efficiency (%)	Power Temperature Coefficient (-% / °C)	Cost (¢/kWh)	Material
1	25.0	High Performance	9	9	9	3	1	1
2	25.0	High Milage	9	9	9	3	1	1
3	20.0	Economy	3	1	3	1	9	1
4	15.0	Stability and reliability	1	1	1	3	3	9
5	15.0	Temperature Durability	1	1	1	9	1	9
Sum	100.0							
		Evaluation= $\sum \alpha_{ij}\, \beta_{ij}$ i= 1,2,..,No.Hows j= 1,2,..,No. Whats	540.0	500.0	540.0	350.0	290.0	340.0
		Relative Weight(%) = Evaluation / ∑Evaluations	21.09	19.53	21.09	13.67	11.33	13.28

Fig. 2. Proposed QFD.

weight, power density, efficiency, power temperature coefficient (PTC), life cycle cost (LCC) of electricity, and material concern.

The specific weight is defined as the total power generated by the PV module divided by the module weight and expressed in watts per kilogram (W/kg). For use in EVs, the specific weight of the PV module should be high, as the installation of PV modules will increase the vehicle curb weight, which affects vehicle performance. The power density is the total power generated divided by the area of the module with units of watts per square meter (W/m^2). Higher density modules are preferred for EVs with limited surface areas. The efficiency of the PV module is defined as the total power generated per unit area (m^2) divided by 1000 W/m^2 and multiplied by 100. The efficiency of the PV module should also be high to provide maximum output power for given weather conditions and given module area. PTC is expressed as –%/°C. An increase in temperature in turn causes a corresponding decrease in all types of PV module performance, with a lower PTC indicating improved performance. Finally, both cost and material criteria will be discussed later.

Second, the "What" window is used to determine VOC preference in an EV. Third, the "Importance" window is used to weigh the VOC preferences as percentages. The higher percentage score represents the most important customer need. Fourth, the "Hows" and "Whats" are combined using a relation matrix that consists of three different scores (1, 3, and 9) to define the relationship between the customer needs and the engineering metrics. Score 1 indicates a low impact between the specific column in the "How" window and a specific row in "What" window; score 3 is the mean medium impact, and score 9 indicates a strong effect. For instance, a score of "25 out of 100" is assigned for "High performance" as a high-valued customer need for those EVs. Any high-performance EV must have a PV with strong power density, specific weight, and PV efficiency, with the medium and weak impacts for the other factors. Correspondingly, the rest of the relationship matrix is completed. Although these values cause decision inconsistency, it can be

reduced by establishing many customer-oriented questionnaires and by incorporating a team of engineering, marketing, and research professionals.

At the bottom, or fifth position of the OFD matrix is the outcome, which is the relative weight. The returned relative weights indicate the relative importance for all PV modules requirements and are used as input to the AHP stage. The relative weight is calculated using

$$\text{Evaluation} = \sum_{\text{ij}} \alpha_{\text{i}} \times \beta_{ij} \tag{1}$$

where i = number of rows (from 1 to 5), j = number of columns (from 1 to 6), α is the importance, and β is the score (the value from the relationship matrix for the given "How"/"What" pair). That is to say, the evaluation in the first column (power density) is calculated as $= 25 \times 9 + 25 \times 9 + 20 \times 3 + 15 \times 1 + 15 \times 1 = 540$.

The relative evaluation is calculated as the specific evaluation divided by the sum of all evaluations that is equal to $540/2560 = 21.09\%$.

B. Stage II: Photovoltaic Search Domain

Here, we highlight the possible search space for the selection process and provide an overview of the different commercial PV technologies with main emphasis on the strengths and challenges of each type of PV module. Although many PV cell types are available, cost, availability of raw materials, reliability, stability, and lifetime limitations limit their widespread availability [19].

The current commercial PV modules are based on bulk silicon (wafer based), and thin films could be deposited on either rigid or flexible substrates. Bulk silicon PV modules in the form of either mono-or multicrystalline silicon (mono-Si or multi-Si) are superior to other PV materials. They are composed of silicon, the second most abundant element in the earth's crust and a well-researched and understood element in the periodic table. Consequently, this element is the predominant material of silicon-based solar cells that compose the $350 billion semiconductor industry, e.g., in 2013, the silicon bulk PV module shipped was 89.58% of a 40 GW total, with thin films [cadmium telluride (CdTe), copper indium gallium selenide (CIGS), and amorphous silicon (a-Si)] solar cells comprising the remaining 10.42% [20]–[23]. Laboratory tests also show that bulk silicon-based single junction cells can achieve an efficiency of 25% [19]. The challenges for CdTe PV modules are that cadmium is toxic, and there is a limited supply of Te [24]. Some companies recycle the product to mitigate environmental toxicity of CdTe modules, but the cost of reclamation is quite prohibitive. CIGS have small amount of cadmium sulfide, making them relatively safer than CdTe PV modules. Unfortunately, CIGS has limited use in that it requires indium, an element that is both rare and expensive [24]. The advantages of a-Si PV module, in addition to the abundance of silicon, is that both the manufacturing tools and techniques used to deposit a-Si and related materials are similar to that used in liquid-crystal display manufacturing. They are also superior to bulk silicon PV modules in terms of PTC. The main disadvantage of a-Si PV module is low efficiency, which can be increased, however, with the use of multiple junction a-Si solar cells.

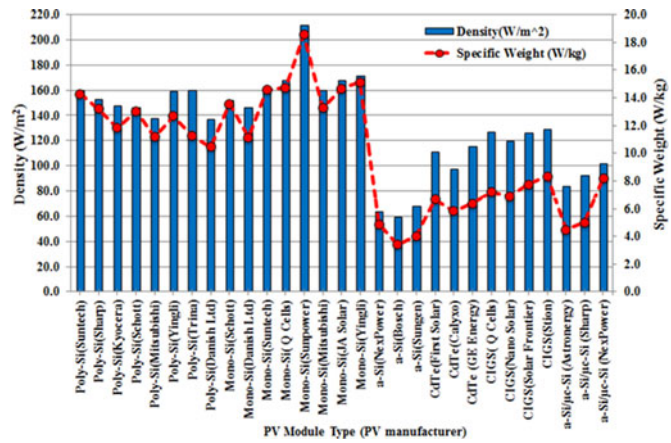

Fig. 3. Power density and specific weight of different PV options from different manufactures.

In this study, we analyzed six different PV module options: mono-Si, multi-Si (poly-Si), a-Si single junction, double junctions' a-Si/micro-Si, CdTe, and CIGS. We did not analyze single and multijunction gallium arsenide (GaAs) (with or without concentration technology), organic photovoltaic (OPV), dye-sensitized solar cell (DSSC), and quantum dot cells. Although GaAs-based solar cells are the most efficient PV type, they are the most expensive and are mainly used in space applications. The relatively low efficiencies of OPVs, DSSCs, and quantum dot cells make them particularly poor candidates for the large-scale PV generation of electricity. Specifically, DSSCs do not exceed 17 cm^2, which makes it very difficult to build large-area energy modules because of the large amount of energy that is lost during their connection [25]. OPV is unreliable with a cell lifetime of only 3 to 4 years [26] compared with other commercial PV module options, which have a lifespan of 20–30 years. Unless there is a fundamental breakthrough in the material synthesis and performance of these types, it is not possible that the PV modules based on these types of solar cells will be ever used for bulk power generation [25].

In order to test the different types of PV module options, we collected the performance specifications for each using manufacturer datasheets and analyzed these data in terms of our decision criteria (see Figs. 3 and 4). More than 20 top PV manufacturers are included in this study, where the best PV module option per manufacturer in terms of maximum power rating is used for analysis that serve as basis for the evaluation. All PV modules included here are rigid. The manufacturer's PV module power ratings are for standard test conditions (STC) (1000-W/m^2 solar irradiance) at 25 °C. Fig. 3 shows the specific weight and the power density of the various PV modules from different manufacturers. Note that both the highest specific weight and the highest power density for the case of mono-Si are approximately 18.5 W/kg and 211.6 W/m^2, respectively. Fig. 4 shows the efficiency and PTC of various PV modules; the efficiency varies from a low value of 5.9% for a-Si modules

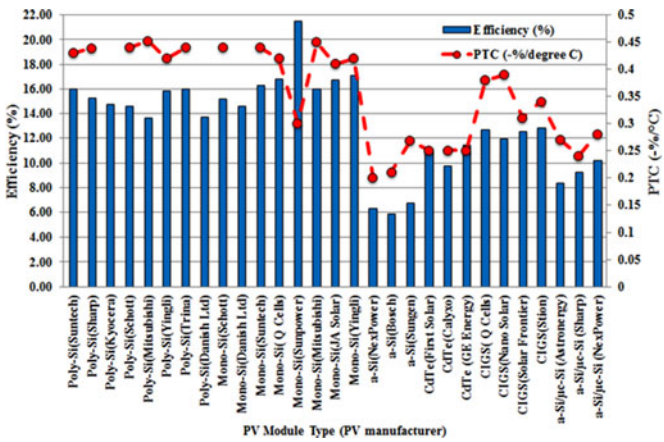

Fig. 4. Efficiency and PTC of different PV options from different manufactures.

TABLE I
DECISION-MAKING PAIRWISE MATRIX

	Alternative					
	Multi-Si	Mono-Si	a-Si	CdTe	CIGS	a-Si/μ-Si
Criteria						
Power Density (W/m^2)	150.1	167.5	63.7	107.9	125.4	92.8
Specific Weight (W/kg)	12.2	14.4	4.1	6.3	7.5	5.9
Efficiency (%)	15.01	16.79	6.35	10.80	12.55	9.30
PTC (-%/°C)	0.437	0.411	0.226	0.250	0.355	0.263
Cost (¢/kWh)	1.871	1.853	1.660	1.652	1.769	1.650
Material	"Excellent"	"Excellent"	"Excellent"	"Least"	"Moderate"	"Excellent"

to a high value of 21.5% for mono-Si. The best PTC value is $-0.2\%/°C$ for a-Si module, and the worst is $-0.452\%/°C$ for a multi-Si module. In Table I, we provide all the values used for the pairwise comparison in stage III. The first four criteria values are the average values shown previously in Figs. 3 and 4. For example, the average specific weight for mono-Si is equal to 14.4 W/kg where this value is the average for all specific weights of mono-Si modules from different mono-Si manufacturers in Fig. 3.

We used this average to 1) enhance the robust nature of our pairwise comparison to reflect actual PV market data and 2) reduce the subjectivity in the traditional AHP method by making the pairwise comparison depend on manufacturer's actual data and not on the evaluations of the decision maker using the 1-to-9 scale [6].

For values of cost criterion in Table I, we used an LCC of electricity indicator for comparison since the constraint here is the installation surface area on the vehicle. The LCC is defined as the total cost of PV system per total energy generated through the PV system in the life cycle in unit ($/kWh). The LCC is calculated using [27, eq. (2) and (3)]

$$\text{LCC (\$ /kWh)} = \frac{\text{Cost} \sum \begin{bmatrix}\text{PV Module} + \text{installation} + \text{land} + \\ \text{Energy storage} + \text{maintenance}\end{bmatrix}}{\text{Total energy generated}} \tag{2}$$

TABLE II
LCC OF ELECTRICITY OF DIFFERENT PV MODULE OPTIONS

	Multi-Si	Mono-Si	a-Si	CdTe	CIGS	a-Si/μ-Si
PV Module price ($/W) (Excluded Tax) [28]	0.655	0.655	0.583	0.583	0.583	0.583
PV Module price ($/W) (with sales tax = 7%)	0.701	0.701	0.624	0.624	0.624	0.624
Cost PV Module ($/m^2)	105.198	117.392	39.737	67.309	78.226	57.890
PV Module Average Lifetime efficiency (%)	13.880	15.640	5.910	10.060	10.920	8.661
Total energy generated (KWh)	5621.400	6334.20	2393.55	4074.3	4422.60	3507.826
Cost PV per Total Energy (¢/KWh)	1.871	1.853	1.660	1.652	1.769	1.650

$$\text{Total energy generated} = \text{I} \times \eta \times \text{PR} \times \text{LT} \times A \tag{3}$$

where I is the irradiation (kWh/m^2/yr) which the average energy flux from the sun and depends on the installation location. η is the lifetime average module efficiency (%), PR is the performance ratio, LT is the system lifespan (year), and A is the total module area (m^2). We did not factor in a cost of land since the PV module integrates into the vehicle body. We also assumed that the installation, maintenance, and energy storage costs were similar for all PV module types. The current prices of commercial PV modules (excluding tax) in ($/W) for the bulk silicon solar modules are 0.55, 0.655, and 0.92, while for thin-film solar modules are slightly less as 0.49, 0.583, and 0.87 for low, average, and high scenarios, respectively [28]. These prices are set by the manufacturers, with Chinese made PV modules the least expensive. The cost of PV module per energy generated is calculated using average module prices, the details of which are given in Table II. The cost of PV module per square meter is calculated using an average module density value (see Table I). The PV module lifetime efficiency is calculated based on degrade over the system lifetime by 0.5% relative to the initial efficiency shown in Table II per year [29]. The total energy generated is calculated using assumed parameters $I = 1800$ kWh/m^2/yr based on US location, $PR = 0.75$, and $n = 30$ years [29].

The use of silicon, which unlike Cd-based CdTe PV modules are neither hazardous to humans nor the environment, obviates any difficulties in the supply chain. Indeed, the CdTe module is not the preferred choice worldwide and may be banned in several countries [30].

Based on material availability/concern, we rank PV module using the traditional 1-to-9 AHP scale [6].

In order to adequately evaluate the PV options, the three constraints (geographical location, mounting configuration, and tracking/orientation option) should be identical in any comparison, which is beyond the scope of this paper.

C. Stage III: Analytical Hierarchy Process

Unlike traditional AHP models, our system evaluates the alternatives differently by first establishing a relationship between the objective function with criterion created by giving related

	Multi -Si	Mono-Si	a-Si	CdTe	CIGS	a-Si/ micro-Si
Multi-Si	1	1.18	0.336	0.516	0.6146	0.4835
Mono-Si	0.847	1	0.2847	0.4374	0.5208	0.4096
a-Si	2.976	3.512	1	1.537	1.829	1.439
CdTe	1.937	2.286	0.6506	1	1.19	0.9363
CIGS	1.627	1.920	0.5467	0.84	1	0.78678
a-Si/micro-Si	2.068	2.441	0.6949	1.068	1.271	1

Consistency index (C.I.) =0.00

Fig. 5. Pairwise comparison matrix related to specific weight.

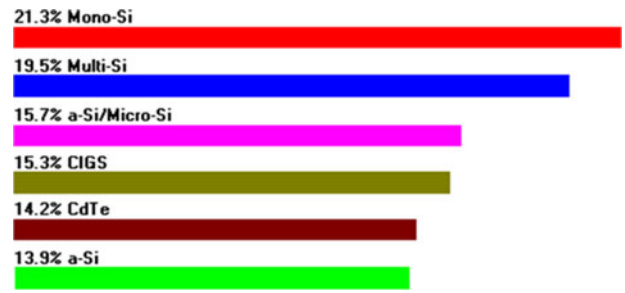

Fig. 6. Rank of different PV modules types for EV application.

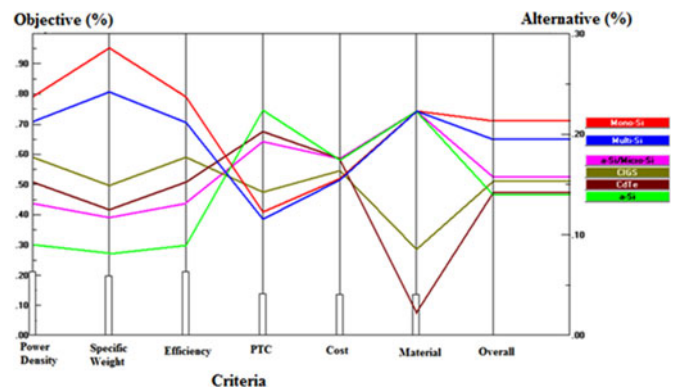

Fig. 7. Performance sensitivity analysis.

weights to each, which we obtain from the QFD stage I output. The relationship between each criterion and each alternative is then established by a pairwise comparison between two elements simultaneously. Table I shows the alternatives, criteria, and the values used in decision. The pairwise comparison matrix A in traditional AHP is obtained based on the decision maker's judgments a_{ij} using the 1-to-9 scale criteria [6, eq. (4)]

$$A = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ a_{21} & 1 & \dots & a_{2n} \\ : & : & \dots & : \\ a_{n1} & . & \dots & 1 \end{bmatrix}, \text{ where } a_{ij} = 1/a_{ji}, i, j = 1,\dots,n. \tag{4}$$

In our proposed methodology, the decision matrix is based on averaging values from actual manufactures datasheets [see Table I]. For example, the pairwise comparison matrix for "specific weight criterion" shown in Fig. 5 has a multi-Si and mono-Si comparison equal to 1.18. This value is calculated by referring to the average specific weights for mono-Si and poly-Si, which are equal to 14.4 and 12.2 W/kg, respectively. By dividing these two numbers, we get 1.18. All comparisons are performed in this manner. Although time consuming, this process yields very accurate results because no personal experiences and opinions of the decision makers are used.

This innovative approach in turn yields a robust decision tool. As the consistency index (CI) is zero, as shown in Fig 5, we can then calculate the CI using the method as follows [6], [31, eq. (5)]:

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1} \tag{5}$$

where $\lambda_{\max}$ is the maximum eigenvalue of the comparison matrix, and n is the number of attributes in the square matrix. In the typical AHP, the conclusion of CI can be drawn by using a comparison to the consistency ratio (CR) to check the judgment of inconsistencies [31, eq. (6)]

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{6}$$

where RI (random index) is an experimental value, which depends on n and represents an average CI for a huge number of randomly generated matrices of the same order. Therefore, CR is the ratio between CI (the calculated value) and the RI (the expected value). The bigger CR requires the decision maker to revise judgments to reduce the inconsistencies. Typically, if the value of CR is less than or equal 0.1, the decision is acceptable [6], [31]. In our case (see Fig. 5), since $n = 6$, then RI $= 1.25$ (The full table of RI values can be found in [31]). Therefore, in a typical AHP, if the CI is less than or equal to 0.125, the decision maker accepts the results. In our proposed methodology, the CI is zero, which, however, reflects the robust and accurate decision-making results. In our final ranking of all the alternatives for the ultimate goal, we found that the crystalline silicon (mono and multi) modules yielded the best overall results, with the CdTe and a-Si PV modules have the lowest results (see Fig. 6).

The performance sensitivity analysis for our problem, shown in Fig. 7, clearly indicates conflicting objectives. Although the mono-Si PV module option yields the best power density, specific weight, and efficiency factors, it is the worst in terms of the cost and the second worst in terms of PTC after multi-Si. Any inclusion of a thin film on a flexible substrate will result in these modules having a higher specific weight. We do not expect these results to vary greatly, however. In addition, any inclusion of semiflexible PV modules with mono- and multicrystalline PV cells between polymer sheets will increase the superiority of these modules as the specific weight of these modules will increase further but with assumption, the cost is still competitive with commercial bulk PV modules.

TABLE III
ASSUMPTIONS FOR EV WITH PV

PV Module SUNPOWER Model: SPR-327 NE-WHT-D	Specifications at 25 °C, Specific Weight = 17.58 W/kg, Density = 200 W/m^2, PTC = –0.38%/°C Efficiency = 20.1%. Total weight of on-board PV with support structure = 25.00 kg Area of on-board PV = 2 m^2 (the constraint is the available installation area on the vehicle) Area of off-board PV = 5 m^2 (the constrain is the required area to charge the battery fully in best case scenario)
Assumptions for scenarios	Best scenario: The temperature in both on-board off-board PV modules at STC (25 °C) Intermediate scenario: On-board PV module at (45 °C) off-board PV modules at STC (25 °C) Worst scenario: The temperature in both on-board off-board PV modules at 45 °C
PV Module Configuration	Horizontal
Operating Location	Insolation = 5 kWh/m^2/day (Average in US) [29]
Typical Lead–acid Battery [33]	Specific energy = 40 Wh/kg Capacity = 7 kWh, Operating window of battery state of charge (SOC) >20% < 80% Batteries weight = 175 kg
Typical lightweight Vehicle Specifications [32]	Traction efficiency (η) = 0.8 Drag coefficient (C_d) X frontal area (A_f) = 0.5 Air density (ρ) = 1.225 kg/m3 Coefficient of rolling resistance (C_r) = 0.008 Gravitational constant = 9.81 m/s^2 Total weight (M) = curb weight + PV weight + driver = 668 kg

IV. ELECTRIC VEHICLES POWERED BY PHOTOVOLTAIC MODULES

Here, we estimate the potential driving ranges for EV powered only by PV modules based on mono-Si PV option, which was ranked first in our study. We also categorized the three scenarios as best, intermediate, and worst cases. The proposed EV is lightweight with an efficient aerodynamic design. For all scenarios, we also assumed that the EV owner has two sets of PV modules and batteries. The first set is of the PV modules are assumed to cover a total surface area of 2 m^2 on the vehicle roof to charge the on-board battery. The other set is assumed to a cover an area of 5 m^2, which will be used to charge batteries at home. The assumptions of the vehicle, PV module, operating location, and battery are given in Table III. For the given vehicle, we calculate the power demands (P_W) at the wheel using the Japan 10+15 driving cycle using [32, eq. (7)–(11)]

$$P_W = \frac{1}{2}\rho C_d A_f V^3 + C_r M g V + M_{\text{eff}} V \frac{dV}{dt} \tag{7}$$

$$M_{\text{eff}} = M + M_r \approx 1.1M. \tag{8}$$

Here, M_{eff} is the effective mass, M_r is the rotational inertia, and V is the vehicle speed, which depends on the driving cycle. The energy to be provided at the wheel over the driving cycle is calculated by

$$E_W = \int_{\text{Cycle}} P_W\, dt = \frac{1}{2}\rho C_d A_f \int_{\text{Cycle}} V^3 dt + C_r M g \int_{\text{Cycle}} V.dt + M_{\text{eff}} \int_{\text{Cycle}} V \frac{dV}{dt}. \tag{9}$$

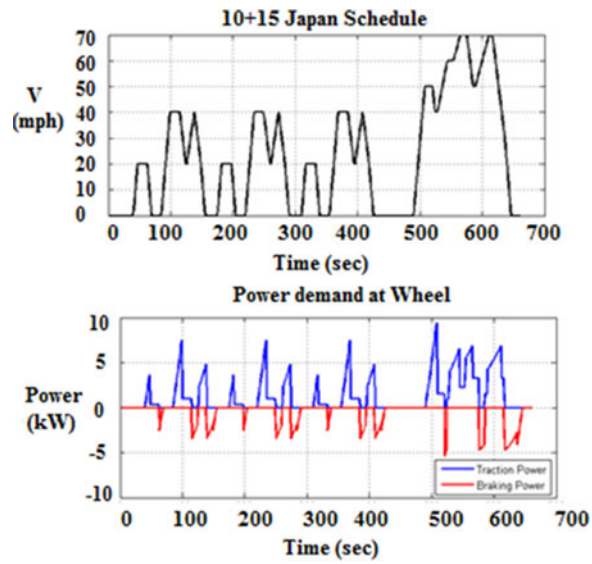

Fig. 8. Driving cycle and power demand at wheel.

Fig. 8 shows the power demands at the wheel and the driving cycle. The driving range (R) is calculated as

$$R = \frac{E_W / D}{E_{\text{batt}}} \tag{10}$$

where D is the driving cycle distance, and E_{batt} is the amount of battery energy that reaches wheel, which is given by

$$E_{\text{batt}} = \eta \times \Delta\text{SOC} \times E_{\text{int}}. \tag{11}$$

Here, η is the traction efficiency and is equal to the product of that efficiency of each component: motor, batteries, etc. ΔSOC is the operating window of the battery state of charge, and E_{int} is the initial energy stored in the battery from the PV, which differs in the three proposed scenarios.

A. Best-Case Scenario

The assumptions of the different scenarios are tabulated in Table III. Here, it is assumed that either with or without efficient cooling, the average temperature on both PV modules is kept at an STC of 25 °C. The power generated by the PV modules at home is equal to 1000 W. In the assumed location, the energy generated by the PV is approximately equal to 5000 Wh per day.

Assuming an ideal case, on the first day, the fully charged EV batteries will provide 5000 Wh of energy storage. On the second day, the second set of PV modules, which is mounted on the car roof, generates 400 W, and the total weight of the modules is 22.75 kg. While driving the EV, the batteries will discharge and will recharge again using the on-board PV modules mounted on the EV. During driving, the EV may not be exposed to sun or the weather may be rainy or cloudy. For these reasons, the amount of energy generated by PV modules mounted on the EV will vary daily. We assume that the PV modules mounted on the EV charge the batteries for 0, 1, 2, 3, 4, or 5 h daily. Adding these additional charges to fully charged batteries provides the EV with the total energy equal to 5000, 5400, 5800, 6200, 6600,

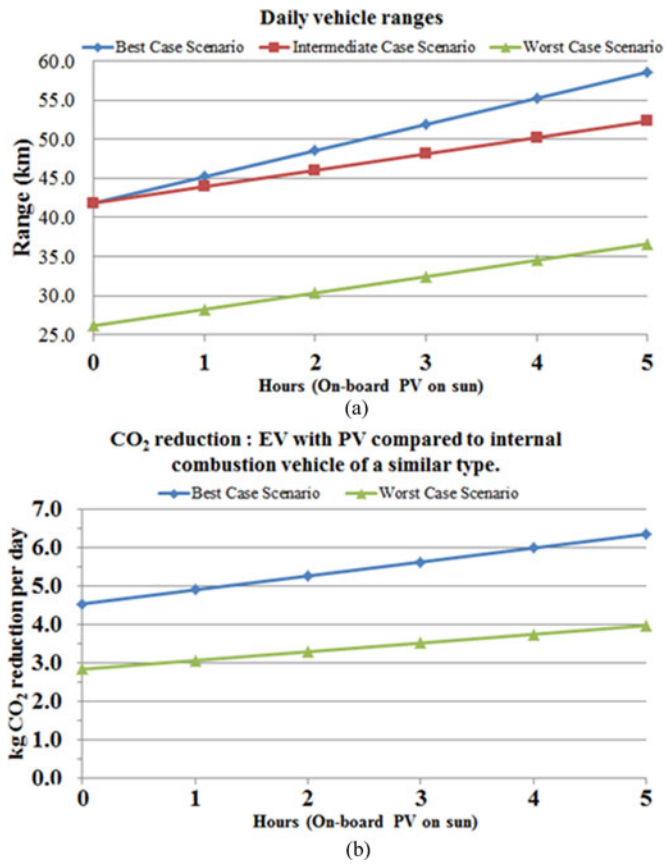

Fig. 9. (a) Daily vehicle ranges of three scenarios. (b) CO_2 reduction compare to equivalent gasoline vehicle.

or 7000 Wh, respectively. To keep the cost of PV-powered EV low, we used lead–acid batteries in this analysis based on [33]. For more sophisticated battery model approach, see [34]. The expected daily vehicle ranges are shown in Fig. 9(a).

B. Intermediate Case Scenario

Here, the PV modules mounted on EV are not cooled. The average temperature in this location is assumed to be approximately 45 °C. Consequently, the PV modules mounted on the EV will provide less electrical power compare with on-board PV module in the best-case scenario. The new efficiency of these PV modules is equal to 12.5% with each generating around 250 W and the car batteries providing additional energy storage of 0, 250, 500, 750, 1000, and 1250 Wh for 0, 1, 2, 3, 4, or 5 h per day, respectively. The expected daily vehicle ranges as a function of vehicle speed are shown in Fig. 9(a).

C. Worst-Case Scenario

Here, the average temperature in both cases (home or if mounted on an EV) is assumed equal to 45 °C. The batteries charged at home provided less energy as compared with the previous cases. The modules will generate 625 W, and the full day charged batteries would store 3125 Wh. The additional charge provided by the PV modules mounted to the battery is identical to the intermediate case scenario. The expected daily vehicle ranges as a function of vehicle speed are in Fig. 9(a).

D. CO_2 Reduction

In Fig. 9(b), we estimate the amount of CO_2 reductions per day for this assumed vehicle compared with an equivalent gasoline vehicle. We estimated the equivalent mile per gallon (MPG) for the assumed vehicle in the given driving cycle as 51 MPG. The calculations are based on [32, eq. (12)]

$$\mathrm{MPG} = \eta_{T2W} \times \frac{\rho_{\mathrm{gasoline}}}{E_{\mathrm{Cycle}}}.I_{\mathrm{Cycle}} \times 2.352 \qquad (12)$$

where η_{T2W} is tank to wheel efficiency (assumed 15%), ρ_{gasoline} is volumetric energy density (assumed 30 MJ/L), E_{cyle} is the energy need for given cycle in MJ, I_{cycle} is the driving cycle length in kilometers, and the 2.352 is the conversation factor. Each gallon of gasoline emits approximately 8887 g of CO_2 [35]. Based on that, our calculation shows that the CO_2 emissions were reduced between 3 and 6.5 kg, compared with internal combustion vehicles of a similar type.

V. Conclusion

Sales of low-speed EVs are expected to increase in the next few years to 695 000 units sold by 2017: a growth of 45% that is not confined to any region of the world [36]. The increase of consumers worldwide who can afford cars makes it most urgent to develop green transportation alternatives. The continued reduction in the cost of PV modules coupled with increase PV module efficiency are the primary impetus for developing electricity-generated PV modules to meet 21st century transportation needs. In this study, with the sole purpose of driving EVs powered only on PV generated energy, we used a unique QFD-AHP hybrid decision-making approach to select the best commercially available PV modules. Unlike traditional methodologies, this unique approach evaluates and ranks the different PV modules by reconciling the conflicting objectives and multi-attribute restraints to solve the problem. The subjectivity inherent in dealing with such tools was reduced with the incorporation of QFD into the input stage to weigh the criteria based on customer's needs and through the use of commercial PV market data for pairwise comparison between alternatives. The subjectivity also can be further limited by establishing a customer-oriented questionnaire and by incorporating a team with members from the engineering, marketing, and R&D departments. The proposed decision-making methodology is robust since we depend on precise data. However, this approach is still useful even in the absence of accurate data. The same methodology can still be applied by making the pairwise comparison between alternatives based on decision maker's experiences. Incorporating many decision makers will reduce the decision subjectivity as well. We found bulk silicon PV modules to be the most appropriate for estimating the driving range for a given set of PV modules and batteries. PV modules are an excellent option powering the next generation of small, lightweight, and aerodynamically efficient vehicles EVs. Future designs for EVs, PV modules, and energy storage units are expected to lead to the commercialization

of low-cost EVs powered exclusively by PV for the entire EV transport industry, making it fully sustainable.

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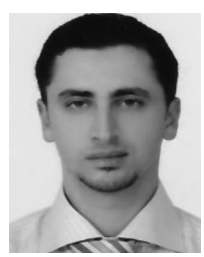

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