UC Merced
UC Merced Previously Published Works

Title
Comparison of an Analytical Hierarchy Process and Fuzzy Axiomatic Design for Selecting Appropriate Photovoltaic Modules for Onboard Vehicle Design

Permalink
https://escholarship.org/uc/item/77k8q66g

Journal
International Journal of Modern Engineering, 15(1)

ISSN
1930-6628

Author
Abdelhamid, Mahmoud

Publication Date
2014

Peer reviewed

COMPARISON OF AN ANALYTICAL HIERARCHY PROCESS AND FUZZY AXIOMATIC DESIGN FOR SELECTING APPROPRIATE PHOTOVOLTAIC MODULES FOR ONBOARD VEHICLE DESIGN

Mahmoud Abdelhamid, Clemson University; Ala Qattawi, University of California, Merced; Rajendra Singh, Clemson University; Imtiaz Haque, Clemson University

Abstract

In this paper, the authors present an overview of the available commercial photovoltaic (PV) module options for powering onboard vehicle applications. The authors used two decision-making methodologies to determine the evaluation factors and the decision-making criteria necessary for assessing the suitability of a particular PV module type. In both the analytical hierarchy process (AHP) and the fuzzy axiomatic design (AD), the authors used at the input stage quality function deployment (QFD) to determine customer requirements for a vehicle with PV module capabilities. This approach is innovative in that evaluation depended upon data collected from PV manufacturers' datasheets. This approach is novel in that: 1) the AHP and fuzzy AD processes were used as decision-making methodologies to select the optimum PV module type to power a vehicle; 2) the QFD and AHP hybrid approaches were compared with the QFD and fuzzy AD hybrid approaches; and, 3) commercial PV market data, not from experts, were used for comparison, as in traditional research. A benchmark of both approaches determined differing results if the evaluation was conducted with both methods using identical data with different natures (i.e., precise versus fuzzy). Results showed that for onboard vehicle applications, the most suitable PV module option was mono-crystalline silicon and the least suitable option was cadmium telluride.

Introduction

Gasoline-powered internal combustion engines have been the mainstay of the automobile industry for over a century. For example, the U.S. transportation sector consumed approximately 71% of the total petroleum used in 2013 [1]. Unfortunately, this technology is now a fundamental hindrance to global economic growth and is entirely inadequate for meeting the long-term energy needs of a growing world economy. The world's population will reach nearly 9 billion in 2040 [2], with a concurrent increase in the number of individuals who can afford vehicles. This population growth will in turn lead to an increase in energy demands, a problem further complicated by the expected increase in petroleum products combined with large and unpredictable fluctuations in availability. Perhaps the greatest adverse effect to the earth's climate is the total energy-related CO_2 vehicular emissions released in that each vehicle emits roughly 5.1 metric tons of CO_2 annually [3].

Switching from the present transportation system to one that uses sustainable, renewable, and clean energy sources will ensure U.S. energy independence with a corresponding low environmental impact. Solar-generated electricity is a prominent candidate for replacing current U.S. energy supplies because of its clean nature, abundance, and supply of inexhaustible and cost-free sunlight. Solar electricity could be generated by photovoltaic (PV) cells, which is a specialized semiconductor diode (PN-Junction) that converts electromagnetic radiation near the visible range into direct current (DC) electricity. The PV module is a packaged assembly of individual PV cells. The cost of PV modules has declined significantly over the past 20 years, from $5.7 per watt in the early nineties to approximately $0.65 per watt currently [4]. The cost of solar electricity will be competitive with other sources of energy by 2020 [5]. As such, the cumulative installed solar PV capacity is firmly moving to the terawatt scale and is a prominent candidate for solving 21st-century energy challenges [6-10]. The continuous increases in PV cell efficiencies [11], improving manufacturing and inspection technologies to make defect-free PV modules [12], and reductions in cost are making PVs particularly useful in powering the next generation of individual transportation solutions. The PV modules can provide energy to the vehicle either via onboard or off-board applications. In off-board applications, the PV is the source of energy for the charging station. In onboard applications, the PV modules are vehicle mounted either to assist in propulsion or to run a specific vehicle application. Applications for onboard PV modules have been the subject of much research. The approaches vary in terms of the configuration and the specifications of the system [13-17].

Thus far, however, no research has been undertaken to determine the decision-making methodology for selecting

COMPARISON OF AN ANALYTICAL HIERARCHY PROCESS AND FUZZY AXIOMATIC DESIGN FOR SELECTING APPROPRIATE PHOTOVOLTAIC MODULES FOR ONBOARD VEHICLE DESIGN

23

the best commercial PV module type for onboard vehicle applications. The objective of this paper was to provide an overview of different commercial PV module options to power vehicle applications, and that of the decision-making criteria for selecting the optimum PV module types for onboard vehicle applications. In this study, two decision-making methodologies were evaluated: the analytical hierarchy process (AHP) [18] and the fuzzy axiomatic design (AD) [19], [20]. In both approaches, the quality function deployment (QFD) [21] was incorporated as the input stage in order to capture customer requirements for vehicle applications with PV module capabilities. The novel use of each of these approaches will benchmark each of the others in order to minimize subjectivity, which usually is the most difficult challenge.

Background of AHP, Fuzzy AD, and QFD

AHP and fuzzy AD are multi-criteria decision-making (MCDM) methods used to evaluate multiple and conflicting criteria. Selecting the best PV module for vehicle applications shares the common MCDM problem characteristics [22] in that the conflicting objective or attribute criteria, and the incommensurable unit of measurements, require choosing a solution from a list of alternatives. The AHP allows decision makers to structure the decision-making case in attribute hierarchies. These establish a relationship between objective function and criteria in the first hierarchy level and between the criteria and alternatives in the second. The AHP is superior in that it combines both qualitative and quantitative approaches. In the qualitative sense, it breaks down an unstructured problem into a systematic decision hierarchy, followed by a quantitative ranking using numerical ranks and weights in which a pairwise comparison determines the local and the global priority weights in order to obtain a ranking of proposed alternatives. Some of the most recent applications of AHP rank various renewable and non-renewable electricity production technologies [23]: selecting the most appropriate package of solar home systems for rural electrification [24]; selecting the solar-thermal power plant investment projects [25]; and evaluating different power plants [26]. As part of this study, the authors used AHP to rank the different micro-crack non-destructive inspection tools for automated PV production stages [27].

Designers can use the AD approach to create a theoretical foundation based on logical and rational thought processes to reduce the random search and trial-and-error processes, and then determine the best design among those proposed designs [19]. The most important concept in AD is the existence of the design axioms [19], [20]. The first axiom, which

is the independence axiom, maintains the independence of functional requirements (FRs). The second axiom is the information axiom, which involves minimizing the information content. The FR is the minimum set of independent requirements that the design must satisfy. The first axiom states that a design solution should not allow one FR to affect the other FRs. The second axiom provides the theoretical basis for design optimization by providing a quantitative measure of the merits of a given design. The design with the least information content is the best choice. The AD was applied to a fuzzy environment in which there were fuzzy data instead of precise data. Some of the applications of fuzzy AD to decision-making problems were selected from renewable energy alternatives [28]: evaluation energy policies [29]; ergonomic compatibility evaluation of advanced manufacturing technology [30]; and, the best green supplier manufacturing companies [31].

The QFD [21] is a method that the designer may use to develop a new product or service by learning about customer needs, which in QFD is 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 attribute in order to set the levels necessary for achieving these characteristics. The QFD tool has been used for many applications [32]. Some authors have used QFD with the AHP tool for various situations [33]. In this study, the authors implemented a QFD and AHP combination as a decision-making tool for selecting materials for automobile bodies [34] and for developing a knowledge-based system to design an automotive production line [35].

Kahraman et al. [36] undertook a comparative study of fuzzy AHP and fuzzy AD and used this approach for selecting the best renewable energy sources, both of which were used in a fuzzy environment with all evaluations based on expert linguistic terms or fuzzy numbers. The proposed approach in this current study goes beyond that work. Unlike conventional fuzzy studies, i) the AHP and fuzzy AD were used for the PV module selection for onboard vehicle application; ii) the pairwise comparison in the AHP depends on data collected from PV manufacturers' datasheets and not numbers from experts, as in typical fuzzy AHP; iii) the fuzzy data applied to AD were from the same dataset, which the authors collected from PV manufacturers; and, iv) the authors conducted a comparative study of the two approaches after adding the QFD as the input stage. There are many other MCDM models, all of which have their strengths, weaknesses, and areas of application, and none of which is truly superior [37]. Thus far, no MCMD has been applied to this current problem and the proposed approaches will fill this gap in the literature. In this study, the AHP and the

fuzzy AD were chosen as the proposed decision-making methodologies for the following reasons: a) it allowed selection of the optimum PV module type for onboard vehicle use, which is an MCMD problem with conflicting objectives; b) it used precise data for a robust pairwise comparison of the AHP decision tool; c) the fuzzy AD approach was used to conduct evaluations in fuzzy environments in order to capture the entire commercial PV market data; d) the QFD can be incorporated into the input stage for both approaches reflecting the VOC and reducing the subjectivity of traditional methods; and, e) the authors used the data from PV manufacturers' datasheets in the proposed evaluation, thus reducing subjectivity and permitting benchmarking of both approaches using data that are both precise and fuzzy.

Methodology

PV Module Types

Though more than 25 PV cell types exist [11], not all are available for commercial use. They are also unsuitable for vehicle applications because of cost, availability of raw materials, reliability, stability, and lifetime limitations. Here, the authors outline the different commercial PV technologies, emphasizing the strengths and challenges of each PV module type. This overview is essential for decision-making as it highlights the possible search space for the MCDM tools. The current commercial PV modules are bulk silicon (wafer-based) or thin films and could be deposited on rigid or flexible substrates. The total global PV module production in 2013 was 40 GW, of which the silicon bulk PV modules (mono-crystalline silicon, Mono-Si, and multi-crystalline silicon, Multi-Si) shipped was 89.58% of the total, and thin films (cadmium telluride, CdTe, copper indium gallium selenide, CIGS, and amorphous silicon a-Si) solar cells comprised the remaining 10.42% [38]. Mono-Si and Multi-Si PV modules are advantageous in that they use silicon, the second most abundant element in the earth's crust. Silicon is also a well-researched and well-understood element in the periodic table, due to its use in the semiconductor industry at around $350 billion.

One of the authors in this study predicted the dominance of silicon as a PV material in 1980 [39]; then restated this prediction in 2009 [40], that the abundance of this raw material is a key requirement for terrestrial PV. CdTe PV modules have the inherent disadvantage of using Cd, which is toxic, and being combined with a limited supply of Te [7]. To handle CdTe module toxicity, some companies recycle this material, but reclamation is both difficult and expensive. CIGS PV modules are much safer than CdTe because

of the miniscule amounts of cadmium sulfide. The most critical drawback of CIGS modules is the very limited supply and expense of indium, which constitutes the primary element of this module [7]. The advantages of an a-Si PV module, in addition to the abundance of silicon, is that the manufacturing techniques and tools used to deposit a-Si and related materials are similar to liquid crystal display (LCD) manufacturing. Additionally, a-Si PV modules also have the advantage of operating well in both hot and cloudy climates and being compatible with building-integrated PVs. The disordered structure of a-Si initially degrades a-Si PV module efficiency, which stabilizes at some point. The efficiency of stabilized commercial single-junction a-Si PV modules is much lower than the single-junction CdTe and CIGS PV modules. However, the performance of commercial double-junction a-Si PV modules is comparable with CdTe and CIGS PV modules.

In this study, the top five commercial PV types were analyzed. Other PV module types—such as multi-junction cells and single-junction gallium arsenide (GaAs) cells, organic photovoltaic (OPV) cells, dye-sensitized solar cells (DSSC), and quantum dot cells—were excluded from this study for the following reasons: Although GaAs is the most efficient PV type, it is also the most expensive, and 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 7 cm^2, which makes it very difficult to build large-area modules because of the large amount of energy lost during connection [8]. OPV is unreliable with a cell lifetime of only 3 to 4 years [41], compared to other PV types, which have a 20-30 year lifespan. In this study, six evaluation criteria were proposed based on QFD, and used for benchmarking and evaluating PV modules for vehicle applications, as below:

(i) Power density, which is defined as PV module power generated per area (W/m^2) at standard test conditions (STC). Limited vehicle surface areas make higher density modules preferable. This factor is related to PV module efficiency, which is the PV wattage generated per area divided by 1000 W/m^2 at STC.

(ii) Specific weight, which is the PV module wattage generated per weight (W/kg). A high specific weight is required, since the installation of PV modules adds extra weight of an automobile body and increases the vehicle curb weight, thereby affecting vehicle performance.

(iii) Power temperature coefficient (PC) is measured as -% per ºC, which is related to PV module reliability. Temperature increases reduce the performance

of all PV module types. A module with a lower PC factor is more reliable.

(iv)   Flexible substrates are used with thin-film technology, making the installation of PV modules on the vehicle body easier.

(v)   Health and safety considerations using silicon obviates any supply chain difficulties. Unlike silicon, Cd-based CdTe PV modules present environmental and human hazards. For that, the CdTe module could be banned in the future in a few countries and is not even a preferred choice worldwide [42].

(vi)   The lifecycle cost (LCC) of electricity is defined as the total cost of the PV system per total energy generated through the PV system in the lifecycle of the unit (¢ per kWh). Given this constraint, the installation surface area on the vehicle is determined as follows, where LCC is calculated using Equations (1) and (2) [43], [44]:

$$LCC(\$/kWh) = \frac{Cost\Sigma\begin{bmatrix}PV\ Module + installation + land +\\ Energy\ storage + maintenance\end{bmatrix}}{Total\ energy\ generated} \quad (1)$$

The total energy generated over a system's lifetime can be calculated using Equation (2):

$$Total\ energy\ generated = I \times \eta \times PR \times LT \times A \quad (2)$$

where, I is the irradiation (kWh/m^2/yr), which is 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 lifetime in a year; and A is the total module area (m^2).

In order to evaluate adequately the PV options, the constraints of geographical location, mounting configuration, and a tracking/orientation option should be identical in any comparison. In addition, the structural design of the solar panels should fulfill many load demands since the solar panels may be subject to strong wind, snow, and many other effects. Aly and Bitsuamlak [45], [46] evaluated wind-induced pressure on solar panels, which are beyond the scope of this paper. In order to evaluate the different PV module types, the authors collected the required performance specifications for each PV module that reflect each of the proposed evaluation factors using datasheets from many PV manufacturers (see Figures 1 and 2). The data gathered from 27 PV manufacturers (eight Multi-Si, eight Mono-Si, three a-Si, three CdTe, and five CIGS) reflect the current PV market. Based on Figures 1 and 2, the results for power density, specific weight, and PC factors are tabulated in Table 1.

Table 1 data are from manufacturers and reflect the minimum and maximum values, and the average values for each PV type. The flexibility and health/safety concerns were non-numerical values. The bulk silicon PV types are rigid, and the thin-film PVs deposited on rigid or flexible substrates depend on packaging. The results, in regards to LCC of electricity (see Table 2), were calculated with the following assumptions: the cost of land was not factored in, since the PV modules were mounted on the vehicle's body. In addition, the installation, maintenance, and energy storage costs were assumed to be similar for all PV module types. The current prices of commercial PV modules (excluding tax) in \$/W for the bulk silicon solar modules were 0.55, 0.657, and 0.92, while thin-film solar modules were slightly lower at 0.49, 0.583, and 0.87 for low, average and, high scenarios, respectively [47]. These prices were set by the manufacturers, with Chinese-made PV modules being the least expensive.
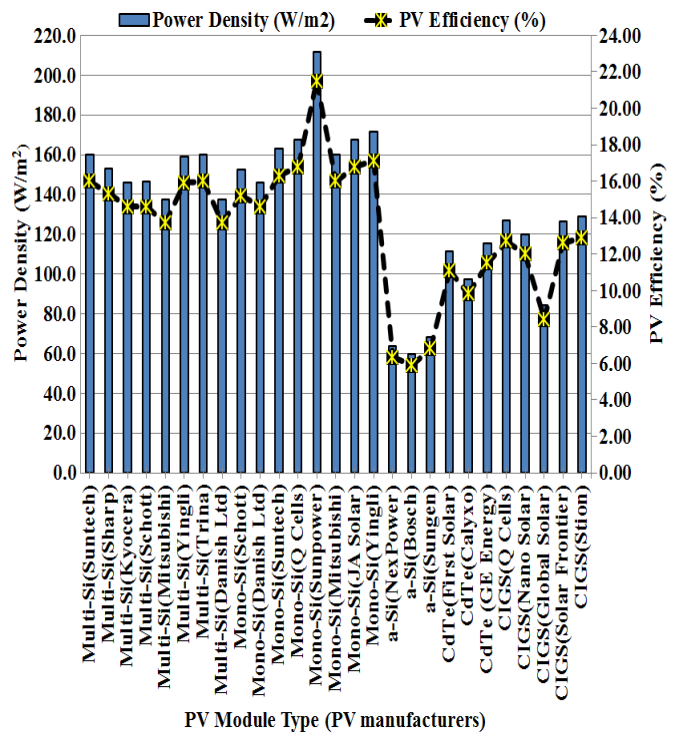

Figure 1. Power Density and Efficiency Factors of the Commercial PV Module Types

The cost of a PV module per energy generated was calculated using three scenarios: best, intermediate, and worst-case. The calculation was based on Equations (1) and (2), and the assumed parameters were I=1800 kWh/m^2/yr, based on U.S. location; PR=0.75; and, n=30 years [48]. Furthermore, η was based on degradation over the system's lifetime by 0.5% (relative to the initial efficiency) per year [48]. The initial PV efficiency was considered equal to the average

PV efficiency in Table 1. Sample LCC calculations are shown in Table 2 with respect to Multi-Si PV modules; the LCC values for all other PV types was done in a similar manner and tabulated in Table 1.
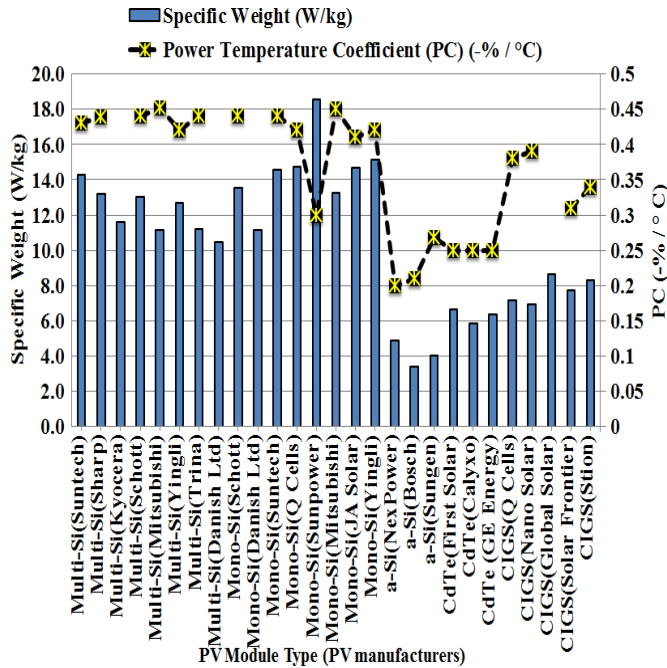

Figure 2. Specific Weight and PC Factors of the Commercial PV Module Types

The QFD and AHP Approaches

The incorporation of the QFD and AHP approaches can be done through a three-step process in order to overcome the well-known dependence of AHP on subjective pairwise comparisons. A knowledge-based database was used in the pairwise comparison, where the comparison of each criterion was based upon manufacturer datasheets. To make the pairwise comparison more robust, the authors compared the average values from different manufacturers of each PV module type in Table 1. Finally, the QFD approach was incorporated as an input stage to the AHP to assign weights per vehicle customer preference. Figure 3 shows the proposed QFD/AHP combined procedure. The QFD structure is shown in Table 3. There are five QFD components. The first are the engineering requirements specified by the *How* window, which are the PV FRs.

Next is the customer need (VOC) represented by the vehicle requirements and specified by the *What* window. Third are the weights for customer needs, shown as an importance percentage of specific vehicle requirements, with the total importance weights for all VOC requirements equaling 100%. Fourth are the combined *How*'s and *What*'s using a relation matrix of three scores (1, 3, and 9), where a score of 1 is the lowest between the specific column in the *How* window and the specific row in the *What* window; a score of 3 is the mean medium impact; and a score of 9 is a strong impact.

Table 1. Performance Data from PV Manufacturers' Datasheets and LCC Results

PV Module Type	Power Density (W/m²)			Specific Weight (W/kg)			PC (-%/°C)			Life cycle cost (LCC) of electricity(¢/kWh)		
	Min.	Max	Avg.	Min.	Max	Avg.	Min.	Max	Avg.	Min.	Max	Avg.
Multi-Si	137.2	159.8	149.9	10.5	14.3	12.2	0.42	0.452	0.4368	1.570	2.625	1.875
Mono-Si	146.1	211.6	167.5	11.1	18.5	14.4	0.3	0.44	0.411	1.557	2.603	1.859
a-Si	59.4	68.2	63.7	3.4	4.9	4.1	0.268	0.2	0.226	1.394	2.477	1.660
CdTe	97.2	115.3	107.9	5.8	6.7	6.3	0.25	0.25	0.25	1.389	2.465	1.652
CIGS	84.1	128.9	117.1	6.9	8.6	7.8	0.31	0.39	0.355	1.389	2.465	1.652

Table 2. LCC Calculations with Respect to Multi-Si PV Modules

PV Module Type	Module price ($/W) (excluded tax) [47]	Module price after 7 % sales tax ($/W)	PV Module Average Power Density (W/m²) [Table 1]	Cost PV Module ($/m²)	PV Module Average initial efficiency (%) [Figure 1]	PV Module Average Lifetime efficiency (%)	Total energy generated (KWh)	Cost PV per Total Energy (¢/KWh)
Low LCC Scenario	0.550	0.589	149.900	88.216	14.900	13.877	5620	1.570
Average LCC Scenario	0.657	0.703	149.900	105.378	14.900	13.877	5620	1.875
High LCC Scenario	0.920	0.984	149.900	147.562	14.900	13.877	5620	2.625

COMPARISON OF AN ANALYTICAL HIERARCHY PROCESS AND FUZZY AXIOMATIC DESIGN FOR SELECTING APPROPRIATE PHOTOVOLTAIC MODULES FOR ONBOARD VEHICLE DESIGN

27

Table 3. Proposed QFD Structure

Relative Weight (%)	Customer Importance	EV Customer Needs / Functional Requirement (FR)	Power Density (W/m²)	Specific Weight (W/kg)	Reliability to Temp.	Envir./health/safety	Flexibility	Cost ($/kWh)
20	3	High Range	9	3	3			
30	2	Help Save Money	9	3	3			9
35	1	Eco-Friendly				9		
15	4	Aesthetic (Good looking)					9	
		Evaluation	450	150	150	315	135	270
		Relative Evaluation (%)	30.6	10.2	10.2	21.4	9.2	18.4

Selection of goal

Selection of alternatives

Collecting data from PV manufacturers ⟷ Selection of criteria

Determine EVs' VOC ⟷ Set weight of criteria using QFD

Pairwise comparison between alternatives per each criterion using AHP
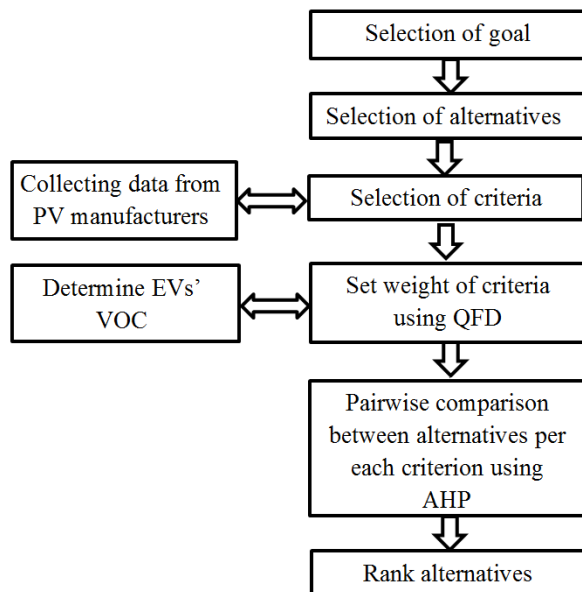
Rank alternatives

Figure 3. Steps for Applying QFD with AHP

For instance, a score of 35 is assigned a label of "Eco-friendly", as a high-valued customer would need for those EVs. EV customer requirements have a strong impact on environmental, health, and safety concerns. Correspondingly, the rest of the relationship matrix can be completed. Although these values cause decision inconsistency, this can be reduced by establishing many customer-oriented questionnaires and by incorporating a team of engineering, marketing, and research professionals. Finally, there is the outcome at the bottom of the QFD matrix of the relative evaluations (weights). In the present approach, the QFD output correlates the PV module FRs with vehicle requirements. The

returned relative evaluations (weights) are the relative importance of all PV module requirements and are the input for the AHP stage. The evaluation was calculated using Equation (3) [21]:

$$Evaluation = \sum \alpha_i \beta_{ij} \qquad (3)$$

where, i = number of rows (from 1 to 4); j = number of columns (from 1 to 6); α is the importance; β is score in specific *How*'s.

The evaluation in the first column (power density) was calculated as = 20×9+30×9= 450. The relative evaluation was calculated as the specific evaluation divided by the sum of all evaluations equal to 450/1470 = 0.306 (30.6%). The last step in this approach entails using AHP to rank alternatives. Figure 4 shows the construction of the problem as a top-level hierarchy, as the objective function of the problem. The second level represents the criteria for evaluations, which is the same *How*'s window in the QFD stage. The third hierarchy level has the alternatives, which are the five PV module candidates.

The proposed AHP model evaluates the alternatives different from traditional AHPs [18]. First, the authors created the relationship between the objective function and each criterion in the first hierarchy, giving related weights for each criterion, which is the output of the QFD stage. Second, the pairwise comparison matrix *A* in a traditional AHP in the second hierarchy was obtained based on the decision-maker's judgments, *aij*, from a scale of 1 to 9 using Equation (4) [18]. In the proposed methodology, the decision matrix was based on averaging the values from actual manufacturer datasheets in Table 1. Table 4 shows

examples of comparisons of PV alternatives, with respect to power density criteria. The comparison between Mono-Si and Poly-Si yielded a value of 1.117.
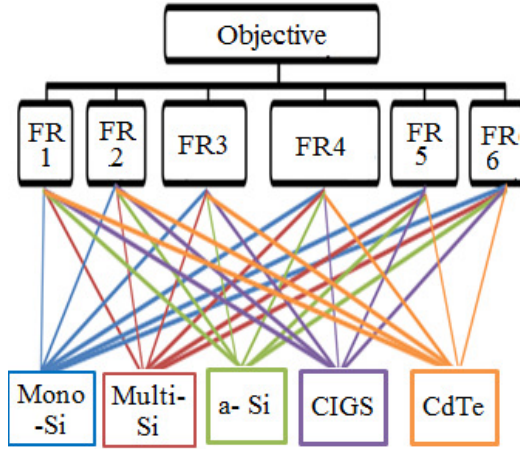

Figure 4. Hierarchical Problem Construction

Table 4. Pairwise Comparison Matrix Related to Power Density

	Mono-Si	Multi-Si	a-Si	CdTe	CIGS
Mono-Si	1.0	**1.117**	2.629	1.43	1.552
Multi-Si	0.89526	1.0	2.353	1.28	1.389
a-Si	0.38037	0.42499	1.0	0.544	0.590
CdTe	0.6993	0.78125	1.8382	1.0	1.085
CIGS	0.64433	0.71994	1.6949	0.92166	1.0

$$A = \begin{bmatrix} 1 & a_{12} & ... & a_{1n} \\ a_{21} & 1 & ... & a_{2n} \\ \vdots & \vdots & ... & \vdots \\ a_{n1} & . & ... & 1 \end{bmatrix} \qquad (4)$$

where, $a_{ij} = 1/a_{ji}$, $i, j = 1,...,n$

The average power densities from datasheets, listed in Table 1 for Mono-Si and Poly-Si, were equal to 167.5 and 149.9 W/m^2, respectively. By dividing these two numbers, the value of 1.117 was obtained (see Table 4). All comparisons were performed in this manner. Although time consuming, the results were very accurate, as no personal experiences of the designers were used. The consistency index (C.I.) was calculated using Equation (5) [49].

$$CI = \frac{\lambda_{max} - n}{n - 1} \qquad (5)$$

Consistency index (C.I.) = 0.00

where, λ_{max} is the maximal eigenvalue of the comparison matrix and n is the number of the attribute in the square matrix.

In this case, $n=5$, as shown in Table 4, since the authors used only actual manufacturer datasheets, and the calculated $\lambda_{max} = 5.00$, and the C.I. = 0.00, as shown in Table 4. In a typical AHP, the conclusion about C.I can be drawn by comparing it to the consistency ratio (CR) in order to check the judgment inconsistencies using Equation (6) [49]:

$$CR = \frac{CI}{RI} \qquad (6)$$

where, RI is the random index, which is an experimental value dependent on n.

In this case, n=5, then RI=1.11 (the full table of RI values can be found in the study by Saaty [49]). In a typical AHP, if the C.I. is less than or equal to 0.111, the decision maker accepts the results; in the proposed methodology, however, the C.I. was zero, which reflects the high accuracy of the methodology used in this study. The final step was to rank all of the alternatives, as shown in Figure 5. The results show that Mono-Si PV modules rank first with a score of 22.9 out of 100 points, followed by multi-Si modules with a score of 21.5 out of 100. The third-, fourth-, and fifth-ranked PV modules were a-Si, CIGS, and CdTe, respectively. The sensitivity analysis of the problem is shown in Figure 6. It clearly indicates that the problem has conflicting objectives. For example, a-Si PV modules have the best results in regards to the PC factor and the worst in both power density and specific weight factors.

The Fuzzy AD Approach

In the second decision-making methodology, the fuzzy AD approach combined with the QFD approach was proposed. The method was based on independence axioms, with information axioms as the decision-selection tool.

Figure 7 lists the steps applied to the fuzzy AD method. The selection of the goal and alternatives were the same as discussed in the AHP decision-making method. Although the FRs were identical to the QFD stage, the first axiom was satisfied. FRs were chosen in order to ensure independence from one another. The system range was set by converting the data in Table 1 to a triangular fuzzy number (TFN) in Table 5. The maximum value was converted to a scale of 10, and the remaining values to a scale of 0-10. The benefits are two-fold: It allows benchmarking the AHP/QFD method, since it uses the same data set; and it provides a robust decision process because it captures the entire commercial

PV market data, and not just the average value used in pairwise comparisons, as with the AHP method. Consequently, decision makers have more freedom to determine which specific PV type satisfies the design range.
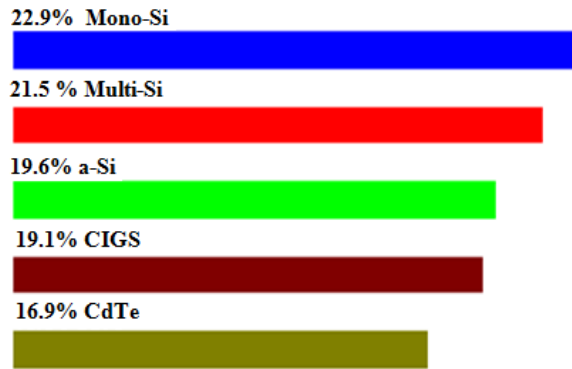

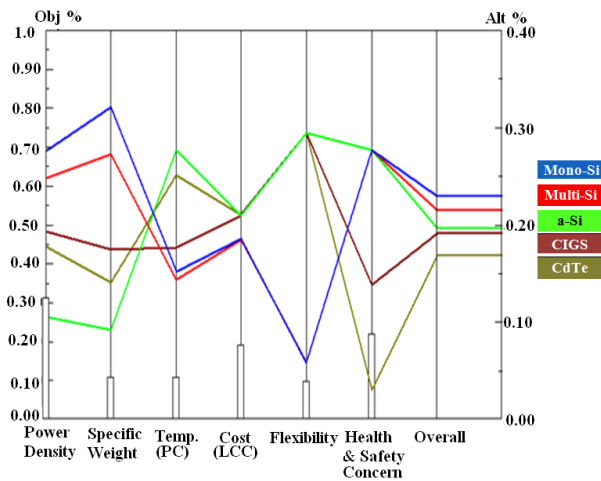**Figure 5. Rank of Different PV Module Types for Vehicle Application using a Combined AHP/QFD Approach**

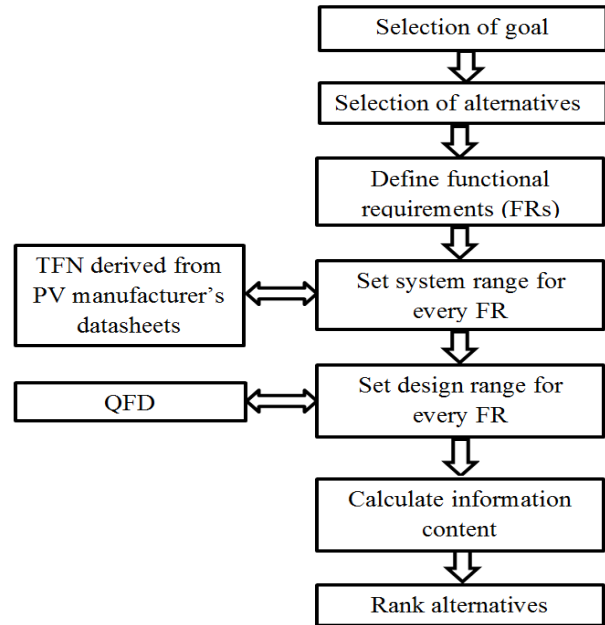**Figure 6. Sensitivity Analysis of AHP/QFD Ranked Results**

Figure 7. The Proposed Approach for a Fuzzy AD Method

In Table 5, the flexibility is set to "0-1-1" if the module is rigid and set to "1-5-10" if it depends upon packaging. For health and safety concerns, value "0" is the best, indicating few adverse environmental consequences. TFN can be defined by a triplet (n_1, n_2, and n_3), shown in Figure 8. The membership function $\mu(x)$ is defined using Equation (7) [50]. For the design ranges for every FR, a wider selection was provided in order to choose the most appropriate alternative for each FR based on QFD. For the factors of power density, specific weight, and flexibly, the highest values are the best for the proposed application. While for all remaining factors—PC, health and safety concerns, and LCC—the opposite is true.

Table 5. System Range for an AD Approach

Criteria	Power Density			Specific Weight			PC			Cost			Flexibility			Health and Safety Consideration		
PV Types	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg
Multi-Si	6.5	7.6	7.1	5.7	7.7	6.6	9.3	10.0	9.7	5.98	10.0	7.14	0.0	1.0	1.0	0.0	1.0	1.0
Mono-Si	6.9	10.0	7.9	6.0	10.0	7.8	6.6	9.7	9.1	5.93	9.92	7.08	0.0	1.0	1.0	0.0	1.0	1.0
a-Si	2.8	3.2	3.0	1.8	2.6	2.2	5.9	4.4	5.0	5.31	9.44	6.32	0.0	10.0	5.0	0.0	1.0	1.0
CdTe	4.6	5.4	5.1	3.1	3.6	3.4	5.5	5.5	5.5	5.29	9.39	6.29	0.0	10.0	5.0	7.0	10.0	10.0
CIGS	4.0	6.1	5.5	3.7	4.6	4.2	6.9	8.6	7.9	5.29	9.39	6.29	0.0	10.0	5.0	4.0	10.0	10.0

$$\mu(x) = \begin{cases} 0, & x < n_1 \\ \dfrac{x-n_1}{n_2-n_1} & n_1 \le x \le n_2 \\ \dfrac{x-n_3}{n_2-n_3} & n_2 \le x \le n_3 \\ 0 & x > n_3 \end{cases} \qquad (7)$$
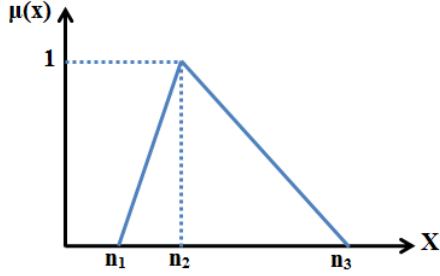
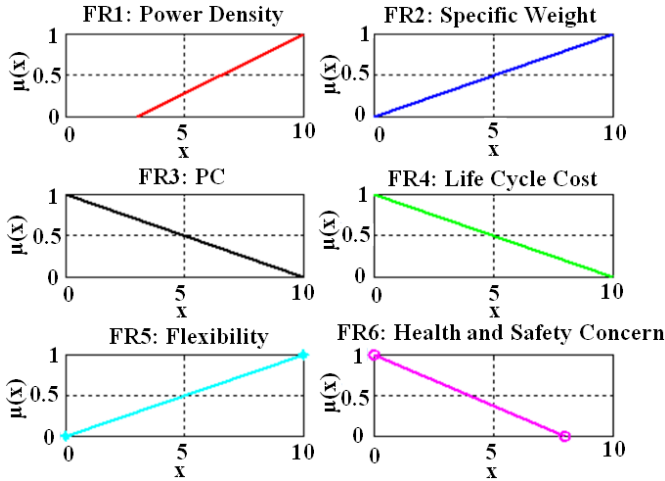

Figure 8. Triangular Fuzzy Number

Figure 9. Design Ranges for an AD Approach

The proposed design ranges in this study are shown in Figure 9. The information content, I_i, for the specific FR_i is defined in terms of probability per Shannon's theory [51], in Equation (8):

$$I_i = \log_2 \frac{1}{P_i} \qquad (8)$$

where, the information, I, is in unit of bits; P is the probability from the AD perspective; and, P_i is the probability of achieving a specific FR_i.

The information content for the entire system was calculated using the Equation (9) [19], [20]:

$$I_{sys} = \sum_{i=1}^{m} I_i = -\sum_{i=1}^{m} \log_2 P_i \qquad (9)$$

where, m is the number of independent FRs.

If the I approach is infinity, the probability is zero and the system will never function. If I is zero, however, the probability is that the system will function perfectly (Axiom 2). In the AD approach, the designer wishes a high probability of success in terms of the design range (tolerance) and system range, which reflects overall system capability. The information content was calculated using Equation (10) [52]:

$$P_i = \frac{\text{Area of common range}}{\text{Area of system design}} \qquad (10)$$

Here, the common range was the overlap between the design and system ranges. For example, the information content was calculated for the "FR3: PC" with respect to an a-Si PV module as an alternative (see Figure 10), which indicated the design ranges (see Figure 9) and system ranges (Table 5). By solving the intersection, the following parameters were determined:

$(x_1, \mu_1) = (4.7159, 0.5284)$
$(x_2, \mu_2) = (5.4946, 0.4505)$

$A_{common} = 0.5559$

$$P_i = \frac{0.5559}{\dfrac{1}{2} \times (5.9 - 4.4) \times 1} = 0.7412$$
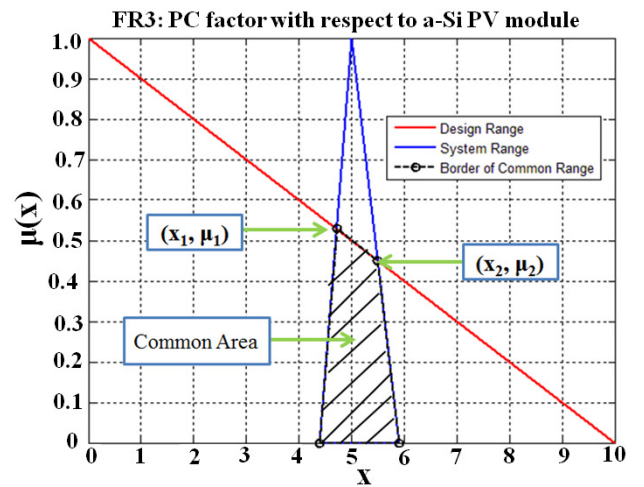
$I_i = \log_2 (0.7412) = 0.432$

Figure 10. FR3 (PC Factor) with Respect to a-Si PV Module

The same procedure was repeated for each FR and each alternative. The calculations for all FRs with respect to all alternatives are tabulated in Table 6. In total, the Mono-Si PV module was ranked first, as it contained the lowest information content followed by the CIGS and Multi-Si PV modules, respectively. The a-Si and CdTe PV modules were fourth and fifth, respectively. The green color in Table 6 indicates the best PV module option for a specific FR. The green color indicates the lowest information content and the best option for a specific FR.

Discussion and Conclusions

Two decision-making methodologies were proposed here for determining the optimum commercially available PV module type for use in vehicle design: (i) a QFD/AHP combination and (ii) a QFD/Fuzzy AD combination. The novel use of both approaches permitted a mutual benchmarking of each with minimal subjectivity, which was the most difficult challenge. In both approaches, the QFD was incorporated in order to correlate the PV module FRs with vehicle requirements. Both were superior to current methods in that the evaluations were dependent on data collected from PV manufacturer datasheets, reflecting current PV market data, which yielded a very robust methodology. The gathered data were used in a pairwise comparison between various alternatives in the AHP methodology and to derive TFN to implement the system range for the fuzzy AD-based approach to capture the complete commercial PV market. The results from the fuzzy AD approach agreed with the AHP results; for both approaches, the most suitable PV was Mono-Si and the least suitable was CdTe. The difference was that, in the AHP approach, the Multi-Si PV modules were ranked number 2; in the fuzzy AD approach, however, the CIGS was ranked number 2. If the aesthetics are deemed less important, as was assumed here, then the crystalline PV was the most appropriate selection. A comparison of both approaches is provided in Table 7.

Table 6. Information Content for Alternatives

PV Type	Power Density	Specific Weight	PC	LCC of Electricity	Flexibility	Health and Safety Concern	Total
Multi-Si	0.26	0.175	3.89	1.43	4.32	**0.02**	10.1
Mono-Si	**0.12**	**0.08**	1.76	1.4	4.32	**0.02**	**7.7**
a-Si	6.18	1.36	**0.43**	1.11	**2.00**	**0.02**	11.1
CdTe	1.01	0.84	1.15	**1.06**	**2.00**	5.05	11.1
CIGS	0.96	0.60	1.36	1.08	**2.00**	2.39	8.4

Table 7. Comparison between AHP/QFD with Fuzzy AD/QFD

Methodology	AHP/QFD	Fuzzy AD/QFD
Approach	Depends upon pairwise comparison based on average value obtained from many PV manufacturers datasheets	Depends on all range obtained from PV manufacture datasheets. Fuzzy data is from the minimum, average, and maximum values in all datasheets.
Way to minimize subjectivity	Each criterion is compared based on actual manufacturer datasheets and not anecdotal decisions. To improve the pairwise comparison, many datasheets are collected from different manufactures with the average for each criterion calculated for each alternative. The QFD is used to weigh all criteria based on customer need and incorporated into the AHP stage.	The FRs and the design range are derived in the QFD stage. System range is derived from manufacturer datasheets in TFN form.
Strength	The inconsistent error is too low. Accurate data is needed to improve the selection of the best PV module.	Robust decision-making tool works in a fuzzy environment

References

[1] Estimated Energy Use in 2013. (n.d.). Retrieved May 12, 2014, from https://flowcharts.llnl.gov/#

[2] The Outlook For Energy: A View to 2040. (n.d.). Retrieved May 1, 2014, from http://cdn.exxonmobil.com/en/energy/energy-outlook

[3] Greenhouse Gas Emissions from a Typical Passenger Vehicle. (n.d.). Retrieved December 1, 2013, from http://www.epa.gov/otaq/climate/documents/420f14040.pdf

[4] Mints, P. (2013, March 20). Solar PV Profit's Last Stand. Retrieved February 4, 2014, from http://www.renewableenergyworld.com/rea/news/article/2013/03/solar-pv-profits-last-stand?cmpid=SolarNL

[5] Photovoltaics. (n.d.). Retrieved February 8, 2014, from http://energy.gov/eere/sunshot/photovoltaics

[6] Martínez-Duart, J. M., & Hernández-Moro, J. (2013). Commentary: Photovoltaics Firmly Moving to the Terawatt Scale. *Journal of Nanophotonics*, *7*(1), 078599-078599.

[7] Singh, R., Gupta, N., & Poole, K. F. (2008). Global Green Energy Conversion Revolution in 21st Century through Solid State Devices. *Proceedings of the 26th International Conference on Microelectronics,* (pp. 45-54). Niš, Serbia.

[8] Singh, R., Alapatt, G. F., & Lakhtakia, A. (2013). Making Solar Cells a Reality in Every Home: Opportunities and Challenges for Photovoltaic Device Design. *IEEE Journal of the Electron Devices Society*, *1* (6), 129-144.

[9] Singh, R., Alapatt, G. F., & Abdelhamid, M. (2012). Green Energy Conversion & Storage for Solving India's Energy Problem through Innovation in Ultra Large Scale Manufacturing and Advanced Research of Solid State Devices and Systems. *Proceedings of the 2012 International Conference of Emerging Electronics (ICEE),* (pp. 1-8). IIT Bombay, Mumbai.

[10] Singh, R., Asif, A. A., Venayagamoorthy, G. K., Lakhtakia, A., Abdelhamid, M., Alapatt, G. F., et al. (2014). Emerging Role of Photovoltaics for Sustainably Powering Underdeveloped, Emerging, and Developed Economies. *Proceedings of the 2nd International Conference on Green Energy and Technology (ICGET)*. Dhaka, Bangladesh.

[11] Green, M. A., Emery, K., Hishikawa, Y., Warta, W., & Dunlop, E. D. (2014). Solar Cell Efficiency Tables (version 43). *Progress in Photovoltaics: Research and Applications*, *22*(1), 1-9.

[12] Tariq, M., Abdelhamid, M., Li, Y., Omar, M., & Zhou, Y. (2012). Fusion of Thermal and Visible Acquisitions for Evaluating Production-borne Scratches and Shunts in Photo-Voltaic PV Cells. *Journal of Materials Science Research*, *1*(4), 57-72.

[13] Fujinaka, M. (1992). Solar Cars Free of Environmental Pollution-Prototype of Practically Usable Car Completed. *Renewable Energy*, *2*(1), 57-64.

[14] Seal, M. R. (1994). Viking 23-zero Emissions in the City, Range and Performance on the Freeway. *Proceedings of the Northcon/94 Conference Record*, (pp. 264-268). Seattle, WA.

[15] Sasaki, K., Yokota, M., Nagayoshi, H., & Kamisako, K. (1997). Evaluation of Electric Motor and Gasoline Engine Hybrid Car using Solar Cells. *Solar Energy Materials and Solar Cells, 47*(1-4), 259-263.

[16] Astrolab. (n.d.). Retrieved January 10, 2014, from http://www.venturi.fr/vehicules/la-gamme-venturi/astrolab/overview

[17] STELLA. (n.d.). Retrieved September 20, 2014, from http://www.stellagoesusa.com

[18] Saaty, T. L. (1990). How to Make a Decision: the Analytic Hierarchy Process. *European Journal of Operational Research, 48*(1), 9-26.

[19] Suh, N. P. (1990). *The Principles of Design*. Oxford University Press.

[20] Suh, N. P. (2001). *Axiomatic Design: Advances and Applications*. Oxford University Press.

[21] Chan, L. K., & Wu, M. L. (2002). Quality Function Deployment: A Literature Review. *European Journal of Operational Research*, *143*(3), 463-497.

[22] Hwang, C., & Yoon, K. (1981). *Multiple Attribute Decision Making: Methods and Application – A State of the Art Survey*. Springer-Verlags.

[23] Stein, E. W. (2013). A Comprehensive Multi-criteria Model to Rank Electric Energy Production Technologies. *Renewable and Sustainable Energy Reviews, 22*, 640-654.

[24] Ahammed, F., & Azeem, A. (2013). Selection of the Most Appropriate Package of Solar Home System Using Analytic Hierarchy Process Model in Rural Areas of Bangladesh. *Renewable Energy*, *55*, 6-11.

[25] Aragonés-Beltrán, P., Chaparro-González, F., Pastor-Ferrando, J., & Pla-Rubio, A. (2014). An AHP (Analytic Hierarchy Process)/ANP (Analytic Network Process)-based Multicriteria Decision Approach for the Selection of Solar-thermal Power Plant Investment Projects. *Energy, 66*, 222-238.

[26] Scannapieco, D., Naddeo, V., & Belgiorno, V. (2014). Sustainable Power Plants: a Support Tool for the Analysis of Alternatives. *Land Use Policy*, *36*, 478-484.

[27] Abdelhamid, M., Singh, R., Omar, M. (2014). Review of Microcrack Detection Techniques for Silicon Solar Cells. *IEEE Journal of Photovoltaics, 4*(1), 514

[28] Kahraman, C., Cebi, S., & Kaya, İ. (2010). Selection among Renewable Energy Alternatives Using Fuzzy Axiomatic Design: The Case of Turkey. *Journal of Universal Computer Science*, *16*(1), 82-102.

[29] Boran, F. E., Boran, K., & Dizdar, E. (2012). A Fuzzy Multi Criteria Decision Making to Evaluate Energy Policy Based on an Information Axiom: A Case Study in Turkey. *Energy Sources, Part B: Economics, Planning, and Policy*, *7*(3), 230-240.

[30] Maldonado, A., García, J. L., Alvarado, A., & Balderrama, C. O. (2013). A Hierarchical Fuzzy Axiomatic Design Methodology for Ergonomic Compatibility Evaluation of Advanced Manufacturing Technology. *The International Journal of Advanced Manufacturing Technology*, *66*(1-4), 171-186.

[31] Kannan, D., Govindan, K., & Rajendran, S. (2014). Fuzzy Axiomatic Design Approach Based Green Supplier Selection: a Case Study from Singapore. *Journal of Cleaner Production.* doi:10.1016/j.jclepro.2013.12.076

[32] Carnevalli, J. A., & Miguel, P. C. (2008). Review, Analysis and Classification of the Literature on QFD—Types of Research, Difficulties and Benefits. *International Journal of Production Economics*, *114*(2), 737-754.

[33] Ho, W. (2008). Integrated Analytic Hierarchy Process and its Applications–a Literature Review. *European Journal of Operational Research, 186*(1), 211-228.

[34] Mayyas, A., Shen, Q., Mayyas, A., Abdelhamid, M., Shan, D., Qattawi, A., et al. (2011). Using Quality Function Deployment and Analytical Hierarchy Process for Material Selection of Body-in-White. *Materials & Design*, *32*(5), 2771-2782.

[35] Qattawi, A., Mayyas, A., Abdelhamid, M., & Omar, M. A. (2013). Incorporating Quality Function Deployment and Analytical Hierarchy Process in a Knowledge-based System for Automotive Production Line Design. *International Journal of Computer Integrated Manufacturing*, *26*(9), 839-856.

[36] Kahraman, C., Kaya, İ., & Cebi, S. (2009). A Comparative Analysis for Multiattribute Selection among Renewable Energy Alternatives using Fuzzy Axiomatic Design and Fuzzy Analytic Hierarchy Process. *Energy*, *34*(10), 1603-1616.

[37] Bouyssou, D., Marchant, T., Pirlot, M., Perny, P., Tsoukias, A., & Vincke, P. (2000). *Evaluation and Decision Models: A Critical Perspective*. Kluwer Academic Publishers.

[38] Mehta, S. (2014). Global 2013 PV Module Production Hits 39.8GW; Yingli is the Shipment Leader. Retrieved April 23 from http://www.greentechmedia.com/articles/read/Global-2013-PV-Module-Production-Hits-39.8-GW-Yingli-Leads-in-Production-a

[39] Singh, R., & Leslie, J. D. (1980). Economic Requirements for New Materials for Solar Photovoltaic Cells. *Solar Energy*, *24*, 589-592.

[40] Singh, R. (2009). Why Silicon Is and Will Remain the Dominant Photovoltaic Material. *Journal of Nanophotonics, 3(1)*, 032503.

[41] Peters, C. H., Sachs-Quintana, I. T., Kastrop, J. P., Beaupré, S., Leclerc, M., & McGehee, M. D. (2011). High Efficiency Polymer Solar Cells with Long Operating Lifetimes. *Advanced Energy Materials*, *1*(4), 491-494.

[42] Saurat, M., & Ritthoff, M. (2010). *Photovoltaics and the RoHS Directive*, Wuppertal Institute, Retrieved from https://engineering.dartmouth.edu/~d30345d/courses/engs171/SauratRittoff-Photovoltaics_and_RoHS-2010.pdf

[43] Ito, M., Kato, K., Komoto, K., Kichimi, T., & Kurokawa, K. (2008). A Comparative Study on Cost and Life-cycle Analysis for 100 MW Very Large-scale PV (VLS-PV) Systems in Deserts Using m-Si, a-Si, CdTe, and CIS Modules. *Progress in Photovoltaics: Research and Applications*, *16*(1), 17-30.

[44] Lakhani, R., Doluweera, G., & Bergerson, J. (2014). Internalizing Land Use Impacts for Life Cycle Cost Analysis of Energy Systems: A Case of California's Photovoltaic Implementation. *Applied Energy*, *116*, 253-259.

[45] Aly, A. M., & Bitsuamlak, G. (2013). Aerodynamics of Ground-mounted Solar Panels: Test Model Scale Effects. *Journal of Wind Engineering and Industrial Aerodynamics*, *123*(Part A), 250-260.

[46] Aly, A. M., & Bitsuamlak, G. (2013). Wind-induced Pressures on Solar Panels Mounted on Residential Homes. *Journal of Architectural Engineering*, *20*(1). 04013003-1, 04013003-12.

[47] PVinsights Grid the World. (n.d.). Retrieved May 5, 2014, from http://pvinsights.com/index.php

[48] Fthenakis, V., Frischknecht, R., Raugei, M., Kim, H. C., Alsema, E., Held, M., et al. (2011). *Methodology Guidelines on Life Cycle Assessment of Photovoltaic Electricity*. (2nd edition). (EA-PVPS T12-03:2011). International Energy Agency Photovoltaic Power Systems Programme.

[49] Saaty, T. L. (1994). *Fundamentals of Decision Making and Priority Theory with the Analytic Hierarchy Process*. RWS Publications

[50] Kaufmann, A., & Gupta, M. M. (1991). *Introduction*

to Fuzzy Arithmetic: Theory and Applications. Van Nostrand Reinhold.

[51] Shannon, C. E. (1948). A Mathematics Theory of Communication. *The Bell System Technical Journal*, *27*(3-4), 373-423.

[52] Kulak O., & Kahraman C. (2005). Multi-attribute Comparison of Advanced Manufacturing Systems using Fuzzy vs. Crisp Axiomatic Design Approach. *International Journal of Production Economics, 95* (3), 415–424.

Biographies

MAHMOUD ABDELHAMID is a Post-Doctoral Scholar at the University of California Advanced Solar Technologies Institute (U.C. Solar) based at the University of California, Merced. He earned his Ph.D. degree from Clemson University (Automotive Engineering, 2014), his M.S. degree from Clemson University (Mechanical Engineering, 2011), and his B.S. degree from Hashemite University, Jordan (Electrical and Computer Engineering, 2004). His research has been published as a one-book manuscript, as well as in more than sixteen journal publications and conference proceedings. His research interests are in the area of sustainable transportation, solar energy, lifecycle assessment, and knowledge-based sustainable manufacturing. Dr. Abdelhamid may be reached at mabdelhamid@ucmerced.edu

ALA QATTAWI is an Assistant Professor at the University of California, Merced. She earned her B.S. degree from Jordan University of Science and Technology, Jordan (Industrial engineering, 2007) and her Ph.D. degree from Clemson University (Automotive Engineering, 2012); she became the first female to earn that degree in the U.S. Her research interest is in innovative manufacturing processes and design, with a focus on Origami-based design and knowledge-based manufacturing. Dr. Qattawi may be reached at aqattawi@ucmerced.edu

RAJENDRA SINGH is the D. Houser Banks Professor in the Department of ECE and the Director of the Center for Silicon Nanoelectronics at Clemson University. He earned his Ph.D. degree from McMaster University, Hamilton, Ontario, Canada (Physics, 1979). His research interests are in the area of semiconductor and photovoltaic device materials and applications. He has published over 350 papers in various journals and conference proceedings. Dr. Singh received various awards, including the White House's "Solar Champions of Change" (April, 2014). Dr. Singh may be reached at srajend@clemson.edu

IMTIAZ HAQUE is Director of the U.S. DOE GATE Center of Excellence in Sustainable Vehicle Systems, Executive Director of the Carroll A. Campbell Graduate Engineering Center, and Founding Chair of the Department of Automotive Engineering at Clemson University. He earned both M.S. and Ph.D. degrees from Clemson University (Mechanical Engineering, 1977 and 1982, respectively). His research interests are in the design, modeling, and simulation of mechanical systems including vehicles and transmissions. Professor Haque has published over 100 refereed papers and has served as PI or co-PI on grants totaling over $100M. Dr. Haque may be reached at sih@clemson.edu