Analyzing consumer acceptance of photovoltaics (PV) using fuzzy logic model

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\textbf{A B S T R A C T}

Consumer perception could play an important role in the adoption of renewable energy technologies. This study aims to explore the role of consumer acceptance and model its effect on residential photovoltaic (PV) adoption. A survey was conducted to understand consumer perceptions of the technology (perception variables), such as perceived cost, perceived maintenance requirement, and environmental concern. To further investigate the adoption potential of residential PV, this paper develops a fuzzy logic inference model to relate consumer perception variables (inputs to the model) to their purchasing probability (output from the model). This model is tested in a case study of residential PV adoption using data from a survey of homeowners in Arizona, United States. The quantitative results of the model demonstrate the role of each perception variable in the consumer acceptance of PV. Public has tended to emphasize on the role of cost reduction in promoting the adoption of residential PV. The results of this study show that other issues such as maintenance requirement and environmental concern are also important.

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1. Introduction

One of the barriers to the adoption of renewable energy technologies has been their relatively higher cost. Policies can be effective to promote renewable energy. In the U.S., the federal and certain state governments, as well as public utilities have adopted incentive policies (such as tax credit and rebates) and regulations (such as renewable portfolio standards) to support the adoption of renewable energy. The cost of electricity generated from residential PV system after subsidies is still higher than that generated from the power grid.

Other than higher cost, many researchers have argued that social and cultural relevant issues are critical barriers [1–5].

Most existing studies have qualitatively illustrated the social acceptance of the renewable energy adoption [1,3,4]. Some other studies quantitatively analyze the relationship of social acceptance and demographic/economic characteristics (such as age, gender, educational level and income) using statistical tools [2,5–7]. However, the attitudes of customers toward renewable energy technologies (such as social familiarity with the technology, environmental awareness) are difficult to quantitatively relate to purchasing probability (or probability of adoption). This study attempts to evaluate the purchasing probability of residential PV system using a quantitative modeling method—fuzzy logic. Fuzzy logic is effective at using linguistic rather than numerical values to describe a problem. Some pioneers have attempted to incorporate this engineering-based methodology into energy related interdisciplinary problems [8,9].

Section 2 presents a literature review of the social acceptance of renewable energy adoption by the public. In Section 3, we illustrate the design of survey and the statistic results of perception variables. In Section 4, we present the methodology of fuzzy logic and the reason we implement it. Then, the fuzzy logic model is applied to process the data from the survey. In Section 5, analysis of the results using the fuzzy logic model is presented. The discussion is in Section 6.

2. Literature review: social acceptance of renewable energy adoption

Researchers, policy decision-makers and industrial investors in this field are attempting to figure out the adoption roadmap of renewable energy technologies and the relevant challenges and opportunities. However, to predict the adoption of renewable energy is highly uncertain, due to technological, economic and social uncertainties. This study will focus on consumer acceptance, so a literature review about social aspects of adopting renewable energy is presented here.

Wustenhagen et al. [1] introduced the issue of social acceptance of renewable energy innovation. It is a summary of the best papers at
an international research conference held in Tramelan (Switzerland) in February 2006. By summarizing the points of view toward social acceptance, the paper presented three dimension of this concept, namely socio-political, community and market acceptance. In this study, we focus mainly on market acceptance (customers’ acceptance). Market acceptance refers to the fact that the role of consumers has changed; they became investors in distributed energy. The ownership of the renewable energy devices, such as solar panels, becomes a question.

In his article [3], Sovacool asked “if renewable power systems deliver such impressive benefits, why do they still provide only 3% of national electricity generation in the United States?” After 181 interviewing with a diverse array of stakeholders, he presented a comprehensive network of impediments from technological, social, political, regulatory, and cultural aspects which he termed as socio-technical. He found that social or cultural barriers are critical, such as, utility operators reject renewable resources because they are trained to think only in terms of big, conventional power plants.

In another article [4], the same author explored the cultural impediments to renewable technologies by conducting interviews at more than 82 institutions. The study found that the apparent disconnect between how electricity is produced and how it is socially perceived perpetuates public apathy and misinformation; also the deeply held values related to consumption, abundance, trust, control and freedom shape American attitudes toward energy. Sovacool noted that psychologists and economists have observed that people hold a strong preference for the status quo. Once they are familiar with a particular energy product, it attains a higher value. This conflict with the view that people will invest in changing their lifestyle if this would maximize self interest.

Other researchers [10] have provided more detailed analysis of the adoption of renewable energy in Denmark and the U.S. Medonca et al. used the term “innovative democracy” to describe the healthy state of renewable energy in Denmark. Not only is the aggregated number impressive, (20% of electricity from wind energy); more importantly, 80% of the wind turbines are owned by households organized in cooperatives. As a result, residents get most of the benefits from investing in renewable energy. The success of renewable energy adoption is to be judged not only by the percent of energy from renewables (e.g., by building large scale of wind or solar farms), but also if it provides more benefits (both environmental and economic) to residents. However, the wide-scale adoption of residential renewable energy technologies faces the social and cultural constraints which more centralized renewable energy technologies may not face.

In one research study conducted by Farhar and Coburn [11], more than 3000 Colorado single-family homeowners in were interviewed about the questions of installing PV system on their roof-top. In terms of favorability of PV systems, the score was 7.5 (out of a possible 10). With regard to familiarity with PV systems, the score was 3.2. The survey also showed that the primary perceived benefit from PV installation is long-term energy cost savings. The most important outcome of this survey is that the main barriers of PV adoption is that residents are not willing to install PV systems until they receive more information (e.g. how they work, how they reduce electricity costs, other users’ experience). Studies of PV adoption based on questionnaire surveys were also conducted in the Netherlands [12], and United Kingdom [13].

Electricity is easily available and inexpensive. In fact, it is hard to notice the existence of power grid. Most customers, except for the few who might be called “tree-huggers”, are unlikely to choose a complicated product even if it might help them to save money. This concern recalls Rogers’ classic model of technology adoption [14] which discusses social acceptance including the consideration of a technology’s relative advantage, complexity and what Rogers called “triability”. Mallett [15] used this model to explained solar water heater adoption in Mexico City emphasizing the importance of cooperation of participants.

Tsoutsos and Staltioulis [16] listed the following barriers to adoption: technological factors, government policy and regulatory framework, cultural and psychological factors, demand factors, production factors, infrastructure and maintenance requirements, undesirable societal and environmental effects, economic factors. Among cultural and psychological factors, he mentioned that unfamiliarity with the new technologies and possible failures or bad examples (broken or run-down wind turbines) lead to skepticism. Besides the qualitative research reports mentioned above, there have been several quantitative analyses regarding the social acceptance of renewable energy.

Zoellner et al. [2] investigated the public acceptance of residential renewable technologies in Germany using statistical regression. Regression analysis of the data shows that the economic costs and benefits of the technology appear to be the strongest predictor of reported acceptance. Furthermore, the importance of landscape evaluation (i.e., visual impact) and a strong connection between procedural justice criteria (including transparency, early and accurate information as well as the possibility of participating during the planning and installation process), and reported public acceptance became evident. Claudy et al. [5] assess consumer awareness of distributed renewable energy, in Ireland. Here, statistical regression revealed the relationship between consumer awareness and demographic variables, such as gender, Internet access, age, household size, employment status. Men, older people, educated people and fully employed people were significantly more likely to have heard of such technologies and have higher awareness of renewable energy technologies.

3. Survey of consumer perceptions of photovoltaic (PV) and statistic results of perception variables

In September 2010 a survey was developed to identify social perceptions of solar electric power technology (PV panels) in the Phoenix Metropolitan Area, Arizona, United States. After a pilot study was conducted to verify the questions, a professional market research company distributed the survey which targeted to homeowners in the category “pro-green energy”. As a “green” technology, solar panels are more likely to be considered acceptable by people with high environmental concern than by the average household. The survey collected 487 completed responses, among them, 454 are non-adopters, 21 are adopters (have installed a grid connected PV). The other 12 respondents are PV adopters but their houses do not use electricity from the power grid. Their PV system is not connected to the grid and their purchasing motivation is considered to be different from grid power customers. Consequently, their responses are not included for analysis in this study.

The questionnaire was designed in two separate parts: one for adopters, the other for non-adopters. The first part of the survey has questions to collect the demographic information of respondents to understand the differences between adopters and non-adopters. The second part has questions to explore the consumer attitudes or perception of PV (in the survey, the term of “solar panels” instead of “PV” was used). The questions in this part were designed to be equipotent. For example, the question on perceived cost, the question for the adopters was “Before you purchased them, did you think that solar panels would save you money over the years you would own them?”; while the question for the non-adopters was “Do you think that solar panels would save you money over the years you would own them?”.

As indicated by the literature review, in addition to higher cost, the convenience of using power grid electricity and lack of familiarity with the solar panels were other important barriers. For
example, power grid customers do not have to worry about the operation and maintenance of power plants; if they install solar panels, they have to take on these responsibilities, at a minimum, to call professionals to address the problems.

To investigate how each factor affecting purchase of PV, the survey asked a question about the ranking of decision-making factors. For non-adopters the question was: “How much would the following factors affect your decision to purchase solar panels?”. For adopters: “How have the following factors affected your decision of purchasing solar panels?”. From the ranking of each factors, cost, break-even time, environmental benefits, maintenance requirement are among the top 4 factors. So they are conceptualized to perception variables as perceived cost (C), perceived maintenance requirement (M), and environmental concern (E).

Fig. 1 to presents a visualized description of the frequency distributions of the perception variables.

The statistical test of survey results (Table 1) indicates that the perception variables differ significantly between adopters and non-adopters.
For the details of the relevant questions of each variable and their scaling, please refer to Table 2.

In order to handle the data using mathematical models (a fuzzy logic model), the scales are stretched linearly to 0 to 10.

The questions in Table 2 were designed to understand the perception of each variable, such as “how do you think the solar panels can benefit environment?”. However, they do not reveal the effects of the variable on customers’ (potential) decision-making process. To understand such effects, a question “How much did the factors affect your decision to purchase solar panels?” was included. Survey responses indicate that adopters consider environment benefit the most important factor in their decision-making (the mean value is 5.81, higher than that of the non-adopters: 5.45); for non-adopters, cost was the most important factor. Table 3 shows the mean values for each variable.

4. Application of fuzzy logic to consumer acceptance (purchasing probability) of PV

To understand the social acceptance of technologies, it is difficult to carry out a controlled experiment to obtain precise data. Moreover, it is not easy to express the problem in a formula and achieve an exact solution. To quantitatively address this issue, it is helpful to use the tool of soft computing, which is good at dealing with complex systems with uncertain information. Such methods include: neural networks, probability (Bayesian) networks, fuzzy logic, expert system, knowledge-based system, and genetic algorithm. The concepts and methodologies of soft computing were originally used in computer science however they are applied to various disciplines, such as medicine, biology, social science and management.

The term fuzzy logic has been used in two different senses. In a narrow sense, fuzzy logic refers to a logical system that surpasses classic two-valued logic for reasoning in a situation of uncertainty. In a broad sense, fuzzy logic refers to all of the theories and technologies that employ fuzzy sets, which are classes with unsharp boundaries [17]. The idea of fuzzy sets was devised in 1964 by Lofti A. Zadeh, a professor of electrical engineering and computer science. Even though there was strong criticism, scholars and scientists in a wide variety of fields—ranging from engineering to sociology—have explored this methodology. During the two decades, fuzzy logic has been implemented broadly in the field of engineering, from fuzzy control to fuzzy model identification. More than 40 years after proposing the concept of fuzzy logic, Professor Zadeh stated “Fuzzy logic may be viewed as an attempt at formalization/mechanization of two remarkable human capabilities. First: the capability to converse, reason and make rational decisions in an environment of imprecision, uncertainty, incompleteness of information, conflicting information, partiality of truth and partiality of possibility—in short, in an environment of imperfect information. Second; the capability to perform a wide variety of physical and mental tasks without any measurements and any computations.” [18].

The core methodology of fuzzy logic is based on four concepts: (1) fuzzy sets: i.e. sets with smooth boundaries; (2) linguistic variables: variables whose values are both qualitatively and quantitatively described by a fuzzy set; (3) possibility distributions: constraints on the value of a linguistic variable imposed by assigning it a fuzzy set; (4) fuzzy if-then rules: a knowledge representation scheme for describing a functional mapping for a logic formula that generalized an implication in two-valued logic.

Some of the existing literature presented the social aspects qualitatively. Other studies related economical and demographic characteristics to social acceptance quantitatively. However none of the existing research has analyzed consumer perception and adoption probability of renewable energy quantitatively. To forecast the future adoption of renewable energy technologies, it would be worthwhile to quantify consumer perception, which is difficult. While some aspects are easily quantified, such as the cost of a PV system; others are not, e.g. familiarity with PV system. We can describe the cost as 1 $/W or 2 $/W, but we can only describe familiarity using language like “I think I feel familiar with solar panels” or “I’m not sure about solar panels”. Linguistic variables can be used to define such statements, which are critical in the methodology of Fuzzy logic to permit descriptions of imprecision in human knowledge [9].

Several published research efforts have tried to implement fuzzy logic to address energy issues.

Kaminaris et al. [8] applied fuzzy logic to assess three renewable energy technologies (PV, wind, small hydro) in terms of their life

<table>
<thead>
<tr>
<th>Perception variable</th>
<th>Questions</th>
<th>Scaling (1–7)</th>
<th>Stretching scales linearly (0–10)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>E (Environmental concern)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adopter</td>
<td>How much do you think solar panels benefit environment?</td>
<td>1: No benefit 7: A lot of benefit</td>
<td>0: No benefit 10: A lot of benefit</td>
</tr>
<tr>
<td>Non-adopter</td>
<td>How much do you think solar panels benefit the environment?</td>
<td>1: No benefit 7: A lot of benefit</td>
<td>0: No benefit 10: A lot of benefit</td>
</tr>
<tr>
<td><strong>C (perceived Cost)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adopter</td>
<td>Before you purchased solar panels, did you think that solar panels would save you money over the years you would own them?</td>
<td>1: Save a lot 7: Cost a lot</td>
<td>0: Save a lot 10: Cost a lot</td>
</tr>
<tr>
<td>Non-adopter</td>
<td>Do you think solar panels would save you money over time?</td>
<td>1: Save a lot 7: Cost a lot</td>
<td>0: Save a lot 10: Cost a lot</td>
</tr>
<tr>
<td><strong>M (perceived Maintenance requirement)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adopter</td>
<td>Before you purchased solar panels, how frequently did you think solar panels would require maintenance from professionals?</td>
<td>1: Once in more than 10 years 7: Several times a year</td>
<td>0: Once in more than 10 years 10: Several times a year</td>
</tr>
<tr>
<td>Non-adopter</td>
<td>How frequently do you think solar panels would require maintenance from professionals?</td>
<td>1: Once in more than 10 years 7: Several times a year</td>
<td>0: Once in more than 10 years 10: Several times a year</td>
</tr>
</tbody>
</table>
cycle cost and emissions. However, they did not emphasize the risks or dynamics of the projects.

Chedid et al. [19] presented a fuzzy multi-objective linear programming approach to solve an energy resource allocation problem. Objectives included minimizing cost, maximizing efficiency, and maximizing the use of local resources. This paper focused mainly on a rural area and most of the electricity consumption could be powered by local resources, such as wood and solar thermal.

Doukas et al. [9] used multi-criteria decision-making and linguistic variables (fuzzy logic) to evaluate power generation technologies. These researchers also developed several improved fuzzy logic methods based on a weighted operator using computer programming.

However, previous research analyzed the features of power system in a static way and did not consider the risks and resilience of the system.

Medina and Morero [20] evaluated risks in the Colombia electricity market using fuzzy logic to consider regulatory risk, electric risk, and social-political risk. However, they focused merely on electricity cost (how risks affect cost), and the risks were specific to Colombia.

Phillis and Andriantiasaholoinaina [21] evaluated the vague concept of sustainability by measuring ecological indicators and human indicators. By using fuzzy logic, the authors were able to combine all these indicators to produce a single, over-all measure. The output of this model was the degree of sustainability of a certain country.

Below we describe the problem of consumer acceptance and the solving method using fuzzy logic step by step.

### Table 3

Effects of the perception variables on decision-making.

<table>
<thead>
<tr>
<th>Perception variable</th>
<th>Mean value of the answers</th>
</tr>
</thead>
<tbody>
<tr>
<td>E</td>
<td>Adopter 5.81 Non-adopter 5.45</td>
</tr>
<tr>
<td>C</td>
<td>Adopter 5.25 Non-adopter 6.26</td>
</tr>
<tr>
<td>M</td>
<td>Adopter 5.42 Non-adopter 4.38</td>
</tr>
</tbody>
</table>

#### 4.1. Problem identification and variables

We are attempting to evaluate the consumer acceptance of residential PV using fuzzy logic by interpreting the results of the survey we conducted. As detailed in Section 3, we know that several perception variables of customers, such as environmental concern (E), perceived cost of solar panels (C), and perceived maintenance requirement (M), differ significantly between early adopter (N1 samples) and non-adopter (N samples).

We define these two groups as:

- A(N1)—Early-adopters
- B(N)—Non-adopters

Each sample has its own characteristics, with the functions (called membership functions) denoted as:

- \( A_i(E, C, M), i \in (1,N1) \)
- \( B_j(E, C, M), j \in (1,N) \)

**Perception variables:**

- E—Environmental concern,
- C—Perceived cost of solar panels,
- M—Perceived maintenance requirement

#### 4.2. Fuzzy logic model structure

The purpose of the evaluation was to determine the purchasing probability (prob) of residential PV among the non-adopters, denoted as: \( B_j(\text{prob}) \)

Fig. 2 illustrates the flow of fuzzy logic methodology. Inputs are survey data from adopters and non-adopters. Outputs are the evaluation of purchasing probability for each sample. The model is constructed by fuzzy logic inference, which will be discussed in detail, step by step. Similar to other mathematical models, the methodology provides a guideline on how to construct the model. To validate the model, parameters and rules have to be tuned to satisfy certain criteria. The criteria are important to control the modeling process. If the criteria are satisfied can it be concluded that the model is useful. Otherwise, tuning of parameters and rules must continue.

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**Fig. 2.** Fuzzy logic inference model for purchasing probability analysis.
The model can be presented as:

\[ A_i \{ \text{prob} \} = \text{Fuzzy logic inference} (A_i \{E,C,M\}), j \in (1,N1) \]

\[ B_j \{ \text{prob} \} = \text{Fuzzy logic inference} (B_j \{E,C,M\}), j \in (1,N) \]

4.3. Fuzzy sets and membership functions

A set in classical set theory always has a sharp boundary. A fuzzy set is a set with a smooth boundary. For example, if the cost of a PV system is $20,000, we can say it is high, and $5000 is low; however, the cost $10,000 is somewhere between high and low. A fuzzy set is thus defined by a function that maps objects in a domain of concern to their membership value in the set. This type of function is called the membership function. The membership function of a fuzzy set \( A \) is denoted as \( \mu_A \), and the membership value of \( x \) in \( A \) is denoted as \( \mu_A(x) \).

The most common shapes of membership functions are triangular and trapezoidal, which are applied effectively and efficiently by fuzzy logic researchers and practitioners. In this study, for each variable \( E, C, M \); the fuzzy set can be \{low, middle, high\}. The shape of membership functions can be triangular or trapezoid. In order to understand the membership functions, use the perceived maintenance requirement (M) of solar panels as an example, we assume:

If \( M \) is less than 2, then we consider it as low
If \( M \) is greater than 7, then we consider it as high
If \( M \) is between 2 and 7, then we consider it as somewhat low and somewhat high (defined using membership function)

We now translate this human language to fuzzy logic.

\[ \text{MatchingDegree} (M, \text{low}) = \mu_{\text{low}}(M) \]
\[ \text{MatchingDegree} (M, \text{middle}) = \mu_{\text{middle}}(M) \]
\[ \text{MatchingDegree} (M, \text{high}) = \mu_{\text{high}}(M) \]

So, for example

If \( M = 1 \); then

\[ \text{MatchingDegree} (1, \text{low}) = \mu_{\text{low}}(1) = 1 \]
\[ \text{MatchingDegree} (1, \text{middle}) = \mu_{\text{middle}}(1) = 0 \]
\[ \text{MatchingDegree} (1, \text{high}) = \mu_{\text{high}}(1) = 0 \]

If \( M = 2.4 \); then

\[ \text{MatchingDegree} (2.4, \text{low}) = \mu_{\text{low}}(2.4) = 0.5 \]
\[ \text{MatchingDegree} (2.4, \text{middle}) = \mu_{\text{middle}}(2.4) = 0.5 \]

\[ \text{MatchingDegree} (2.4, \text{high}) = \mu_{\text{high}}(2.4) = 0 \]

If \( M = 8 \); then

\[ \text{MatchingDegree} (8, \text{low}) = \mu_{\text{low}}(8) = 0 \]
\[ \text{MatchingDegree} (8, \text{middle}) = \mu_{\text{middle}}(8) = 0 \]
\[ \text{MatchingDegree} (8, \text{high}) = \mu_{\text{high}}(8) = 1 \]

The membership functions in this study are shown in Fig. 3.

4.4. Fuzzy If-Then logic inference

After the fuzzy variables and membership functions have been defined. The next step is to define If-Then logic inference.

For example, if the relative cost of solar panels is low, the familiarity of solar panels is high, the moving frequency is low and

<table>
<thead>
<tr>
<th>If ( E ) AND ( C ) AND ( M )</th>
<th>Then Probability</th>
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<tbody>
<tr>
<td>high</td>
<td>low</td>
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<tr>
<td>middle</td>
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<td>low</td>
<td>low</td>
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<td>middle</td>
<td>high</td>
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<tr>
<td>low</td>
<td>high</td>
</tr>
</tbody>
</table>

Table 4

Rules of fuzzy logic IF-THEN inference.
environmental awareness is high, then the acceptance of this technology is considered to be high logically.

To translate this reasoning into fuzzy logic:

If E is high, AND C is low, AND M is low,
Then probability is very high (5).

If E is middle, AND C is low, AND M is low,
Then probability is somewhat high (4).

If E is low, AND C is low, AND M is low,
Then probability is neutral (3).

If E is low, AND C is high, AND M is low,
Then probability is somewhat low (2).

If E is low, AND C is high, AND M is high,
Then probability is very low (1).

Because the fuzzy set of each variable has three values {high, middle, low}, and there are three variables (E, C, M), there are 27 (3 * 3 * 3) combinations. We may also define the probability in the following way: {100%, 75%; 50%; 25%; 0%} = \{5,4,3,2,1\}.

Table 4 shows the rules of fuzzy logic reasoning which have been tuned for validity.

The steps in this methodology, listed above, define the functional operations of fuzzy logic. The function of fuzzy logic reasoning is like an engine, now we fuel the engine with input data to make it run.

For a fuzzy system whose final output needs to be crisp, a step is needed to convert the final combined fuzzy conclusion into a crisp one. This step is called defuzzification. There are two major defuzzification techniques: (1) the Mean Maximum (MOM) method and (2) the Center of Area (COA) (Yen and Langari, 1999, p.44).

4.5. MATLAB programming and tuning of rules

This study used a software toolbox in MATLAB: Fuzzy logic Toolbox, especially the Fuzzy Inference System (FIS) editor. It provides default parameters of membership functions (the shapes are chosen by modelers). The membership functions are shown in Fig. 3. We did not tune the parameters because the default values can satisfy the criteria. In practice, rules are usually tuned first in models, then membership functions. The criterion for validating the model is to maximize the difference between the mean values of the two groups. By adjusting the membership functions and

![Fig. 4. Purchasing probability distribution using the fuzzy logic model.](image)

![Fig. 5. 3-D purchasing probability scattering using the fuzzy logic model.](image)
rules, modelers accumulate expertise in modeling. As a result, a maximized difference of 30% can be achieved.

5. Results and analysis

Fig. 4 shows the purchasing probability distribution after model validation. The peak of the purchasing probability distribution of adopters is at 100%, for non-adopters, it is at 20%. The difference between mean value of the probability is 30%.

Fig. 5 shows a 3-D graph of purchasing probability of both adopters and non-adopters with the variables. The three variables represent the X, Y, Z axes, while the size and color of the scattering dots represent the probability (the larger and lighter the dot, the higher the probability).

6. Discussions

Many variables affect customers’ decision-making process of purchasing solar panels. The customer attitudinal survey showed that the top three variables are perceived cost (C), perceived maintenance requirement (M) and environmental concern (E). Here we identify them as perception variables. The statistics test shows significant differences between adopters and non-adopters. The fuzzy logic model shows results (Fig. 4) with the purchasing probability distribution for adopters approaching 1.0; this is because the adopters have already made the purchase. We developed and used a model of fuzzy logic inference. The purchasing probability distribution of adopters and non-adopters is the output of the fuzzy logic model (Fig. 5).

We discussed the relationship between purchasing probability and the three variables. However, many other variables affect customers’ attitude, for example, the survey shows plans to move, esthetics of solar panels, availability of financial programs and regulation from Homeowner Associations are among the factors affecting consumer perception. In the future, a more advanced fuzzy logic model can be developed to include more variables. The fuzzy logic inference model provides an alternative solution to address the social issue of technology adoption. However, due to its ability to deal with imprecise and insufficient information, it also has potential in other domains of social science.

One important caveat in the study is data limitation. The sample for adopters was relatively small (since adoption of PV is at an early stage). To validate the model and provide policy direction, a larger sample is required for further survey study. This study has explored the applicability of soft computing model to social acceptance issues, and discussed potential policy implications. To make concrete policy suggestions, more work is needed in the future, both with regard to data (larger sample) and methodology (more delicate model).

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