PLUG-IN ELECTRIC VEHICLE OWNER BEHAVIOUR STUDY USING FUZZY SYSTEMS

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Abstract

In this paper, we focused on one of the important aspects of plug-in electric vehicle (PIEV) use: the PIEV owners' behaviour modelling. In order to investigate the effect of several factors on owners' behaviour, having a set of historical data about the customers is necessary. For this purpose, a questionnaire has been designed in Google spreadsheet and the output results of this data collection have been used for modelling purpose. Firstly, the collected data was sorted and shown in a fuzzified format based on the final decision-making concept. In the next step, fuzzy rules are defined to calculate the customer acceptance index (CAI) based on four fuzzy inputs: cost of electricity (CE), cost of fuel (CF), fast/slow charging penetration (FSP) and controlled/uncontrolled charging penetration (CUP). Finally, the results have been shown in terms of CAI value which is an integer in the [0,1] interval.

Key Words

Plug-in electric vehicle (PIEV), customer behaviour modelling, Fuzzy system utilization, customer acceptance index (CAI)

1. Introduction

Reducing greenhouse gas emissions, rising fossil fuel prices and other incentives for independence from fuel price have been the motivations for the development of future power system, called smart grid (SG). Plug-in electric vehicles (PIEVs) are one of the most important elements of SG. PIEVs have less environmental pollution, higher efficiency and less noise pollution; therefore they will be welcomed by consumers. Figure 1 shows some of the most influential elements of SG.

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In [1], a PIEV load profile modelling approach is introduced based on four exigent factors: vehicle type, distance, charging level and charging start time. The major contribution of this project is the customer behaviour modelling using fuzzy systems and considering all of the

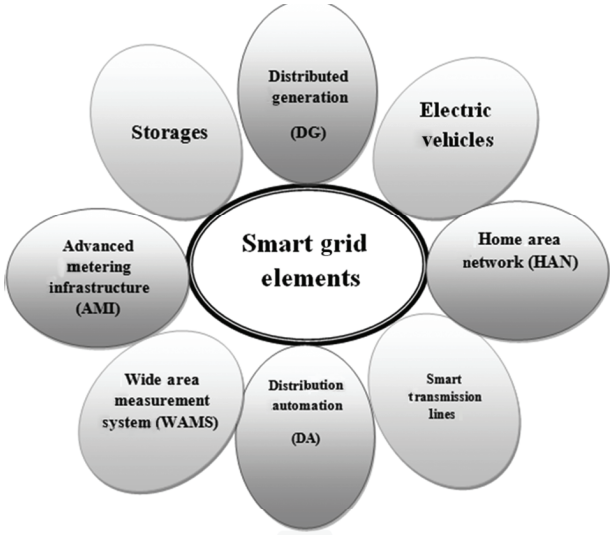

Figure 1. General framework of smart grid [2].

influential factors on behaviour of PIEV owners. Investigations have also been done on the effect of charging profile on distribution network [3]. In the literature, there are few studies which have considered the behaviour of PIEV owners [4]. To represent the importance of this project, Fig. 2

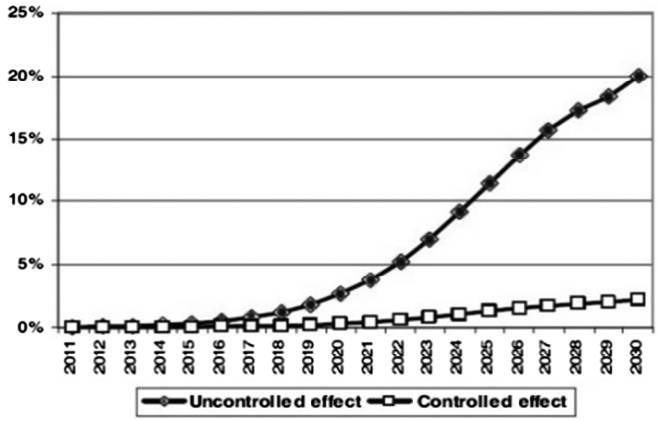

Figure 2. Predicting the peak increasing due to controlled and uncontrolled charging.

$$\mu_A(x) = \begin{cases} 0, & (x < a) \text{ or } (x > d) \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \end{cases}$$

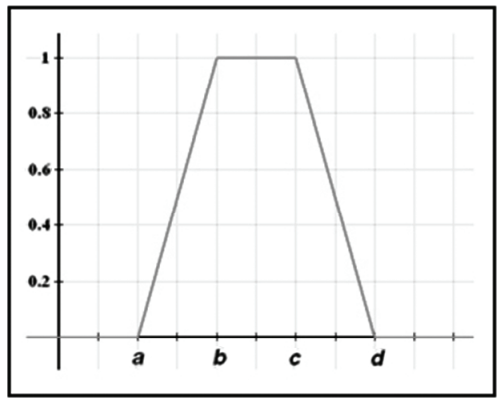

Figure 3. Fuzzy trapezoidal membership function.

corresponds to a gradual increase in the number of PIEVs, where the impact of controlled and uncontrolled charging curve at the peak load is shown [5]. Mathematical modelling of PIEV customers is studied in [6], [2]. Additionally, modelling the EV parking lots is also studied in [7], [8]. According to [9], a game-theoretic charging algorithm has been proposed for EVs.

The remainder of this paper is organized as follows: Section 2 introduces the proposed method for modelling the PIEV owners' behaviour using fuzzified effective factors. In Section 3, the proposed method is implemented based on the questionnaire-based data collection. Section 4 concludes the paper and Section 5 presents the references which are used to define the proposed framework.

2. Fuzzy Logic Utilization in Customer Behaviour Modelling

In general, modelling of PIEV customer behaviour does not follow a crisp decision pattern. Furthermore, with four distinct sets of constraints, simply computing a binary product of each would not produce an output with a great deal of meaning. Through the introduction of a decision base that can integrate all four characteristics in parallel on a sliding scale, one can converge on an index which would assign a number between 0 and 1 to describe the ideal customer conditions for charging. For this purpose, fuzzy logic presents an excellent tool to deal with the reasoning base involved in such a complicated decision [10]. The binary or crisp cases presented earlier are converted to a sliding scale between 0 and 1. The sliding scale is further modified with membership functions placing a mathematical meaning over the most common user opinions collected during the questionnaire. We are also able to model and differentiate the overlap in opinion which occurs in the range of the user opinion. For example, a majority of users may place the charging rate as a linear digression model of importance between the hours of 09:30 and 16:00, but during 09:30 and 14:00 we also find a great deal of users who place an average (normal) importance on the charging rate. The use of fuzzy logic membership functions will allow us to mathematically interpret this overlap. For this reason, we have selected to define the user opinions for each of the four inputs using trapezoidal

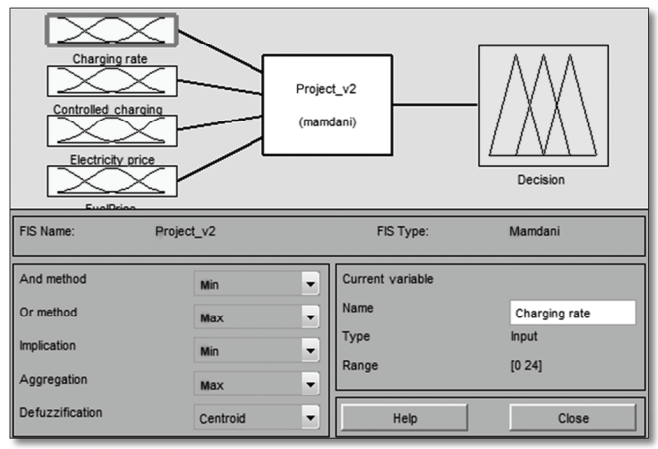

Figure 4. MATLAB fuzzy logic toolbox.

membership functions such as the one shown in Fig. 3. These relatively simple membership functions will allow us to select a, b, c, and d in terms of the time of day. By shifting a and d, we can modify the slope of the membership function and model the overlap of user opinions over the importance of each feature over a certain period (d-a) of the day.

3. Implementation

To fuzzify the problem based on the owner preferences, a questionnaire was distributed using a Google spreadsheet. People were asked to determine their preferences in charging the PIEV and answer the questions qualitatively. A sample day was divided to eight intervals, and four effective pain decision-making were asked to be answered for each of these intervals. Based on the results of the participants, a fuzzified input was constructed for each index of the electricity price, fuel price, fast/slow charging, and controlled/uncontrolled charging. For each index, a membership function was assigned to the expressions of "not important", "normal", and "important". Complex system behaviours can be modelled using simple logic-based rules which can be implemented into a fuzzy inference system. The toolbox is separated into three distinct parts: input, rules, and output. The toolbox for this project is shown in Fig. 4.

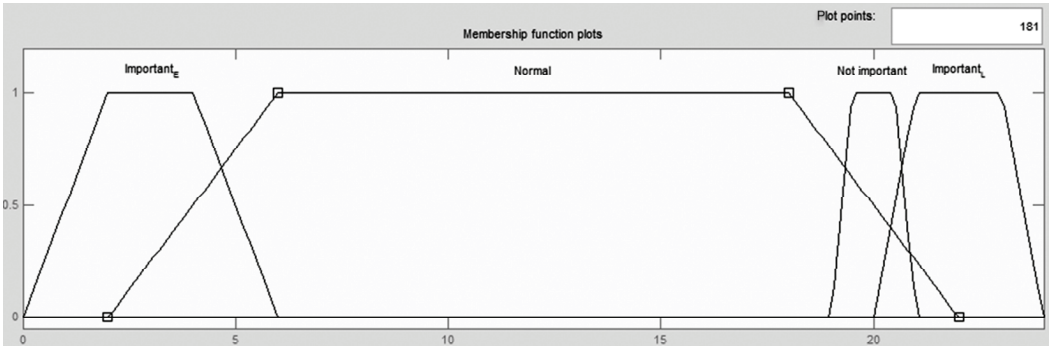

Figure 5. Fuel price Fuzzification.

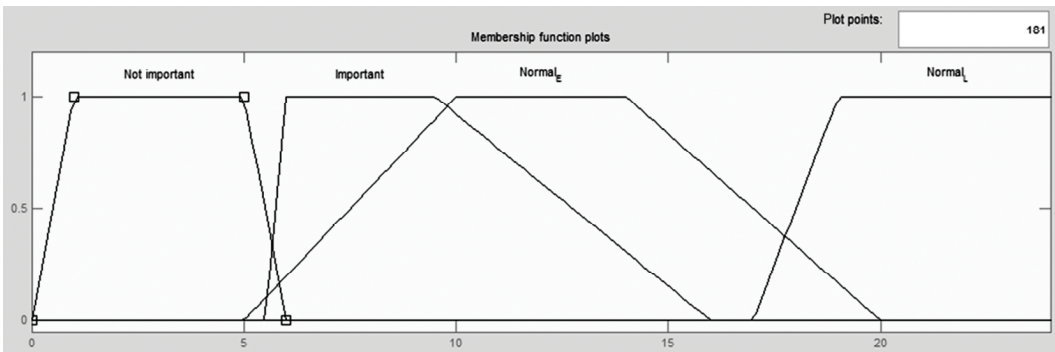

Figure 6. Charging rate fuzzification.

All membership functions define the user consensus of importance over a 1-day period from 0–24 h. Each input has its own respective distribution defining which periods were the most important for each. All membership functions have been defined using the trapezoidal method as described previously.

- Electricity Price: Electricity fuzzification reveals that the user opinion over the most important times to be charging actually occur early in the morning and late in the evening. In the morning, a small period of time transitions sharply into a less important feature with a minor overlap. This is most likely due to this period falling during typical commuting times in the morning which would vary person to person. For a majority of the day, the general opinion places a mixed opinion (normal) on whether the electricity price is an important factor.
- Fuel Price: The fuel price membership function plot is shown in Fig. 5. This plot reveals once again a split between the importance of the fuel price in the morning and the evening. The period of equal (normal) importance operates over a majority of the day most likely due to users having already arrived at work and if they require the use of fuel, it would be for shorter distances. The period of non-importance shifts to later in the afternoon, but once again it follows a sharp and short period. As an alternative to the morning rush hour, we see the fuel price concerns drop in the afternoon as users are most likely eager to return home without major care over the cost of fuel.
- Charging Rate: The charging rate membership function plot is shown in Fig. 6. This plot presents a very different distribution from that of the previous inputs. User importance over the charging rate is indicated as most important during the morning commute with a gradual falloff for the rest of the day. Over the same time, user consensus found that a number of people placed no importance on the charging rate during the day. This complex relationship of user opinion has a significant contribution to the output membership surface shown later.
- Controlled Charging: This fuzzification is less complicated than that of the charging rate as for a majority of the hours of the day; the user is not concerned with the controlled or uncontrolled charging. The important and unimportant periods share common time periods and are close to one another, thus the overlapping region is complex and also contributes significantly to the decision surface.

4. Mamdani Decision-Making and Rules

The Mamdani-type inference system was chosen to develop output functions for this project. Proposed in 1975 by Ebrahim Mamdani, this is the most common fuzzy methodology involving the selection of a set of logical rules processed with AND and OR comparisons [11]. The inputs are then fuzzified using the defined membership functions and combined according to the rule set. Seven rule sets have been defined for this project. The fuzzy rules are

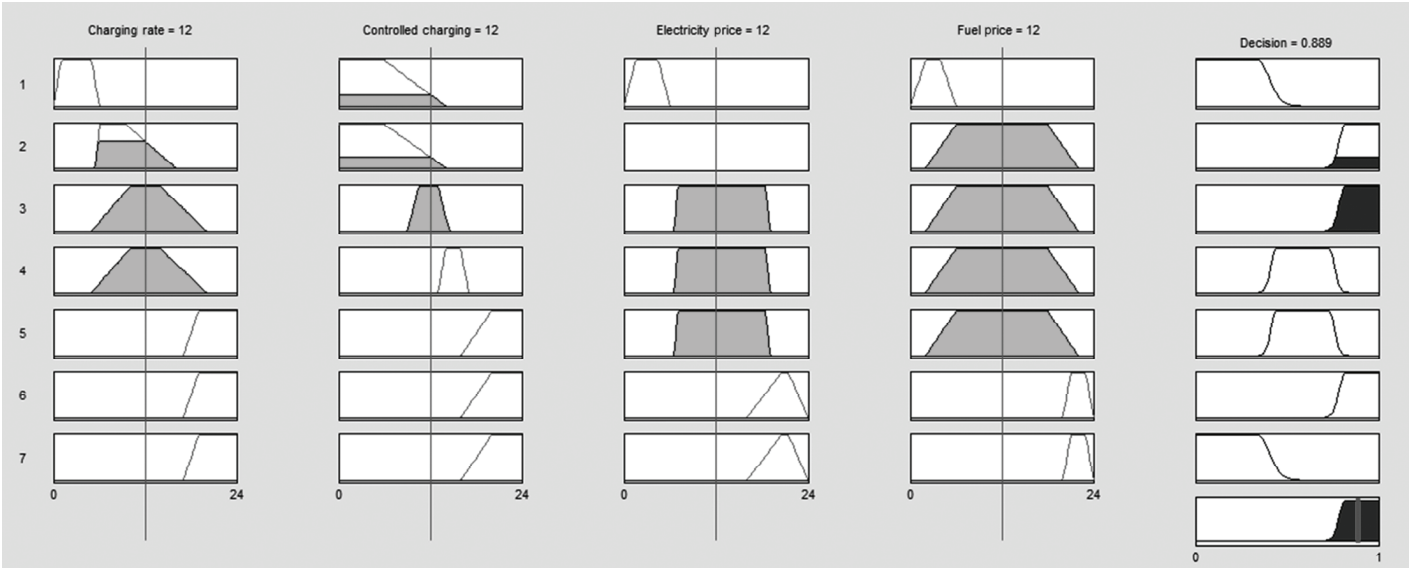

Figure 7. Fuzzy rule output simulation.

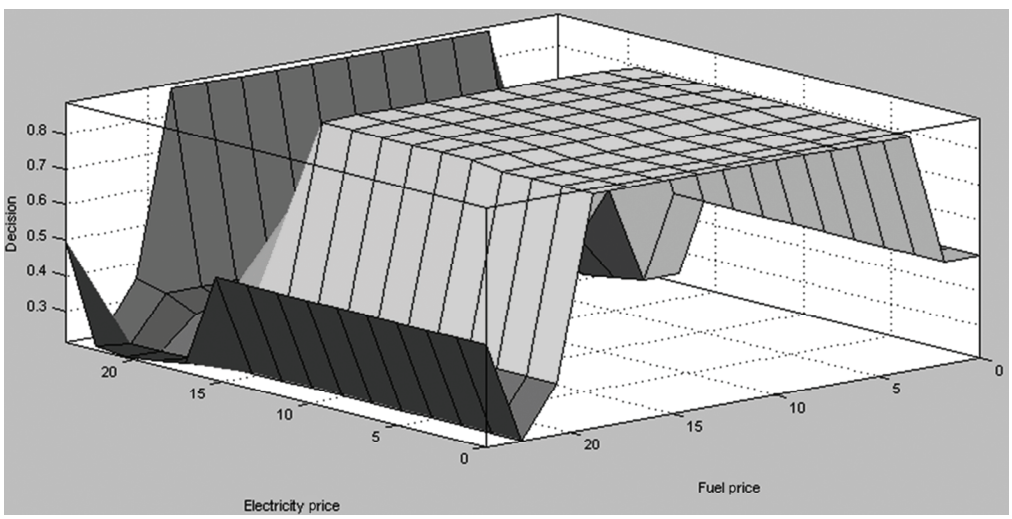

Figure 8. Fuzzy surface view of electricity price versus fuel price.

then combined to establish the strength of the rule and consequence for its selection which produce the output distribution. The output distribution is then defuzzified according to the output membership function.

Rules View: Following the configuration of the fuzzy system, two methods can test and depict the decision output characteristics. Shown in Fig. 8, each input is displayed pictorially with a membership function corresponding to that time period as well as the contribution to the final decision system. Seven cases of each input are shown relating to each rule. To test this system, all inputs step through hourly and provide the customer acceptance index (CAI) output numerically and pictorially. In the case shown in Fig. 7, all inputs are configured to calculate the CAI at 12 noon. The decision block shows 12 noon corresponding to a very high CAI of 0.889.

Surface View: Another powerful tool to analyze the final fuzzy system is by looking at a three-dimensional decision surface. Since only three dimensions can be visualized at each time, and only two of four inputs are included for comparison, a number of independent surfaces must be generated.

A comparison case is shown in Fig. 8 depicting the difference of the output decision with respect to the electricity and fuel prices. This surface contains some drastic, sharp height differences but presents a distinct platform in which the two meet favourably to produce a high CAI. Once again, the CAI range employs >70% of the range.

Hourly Decision Output: Table 1 displays a bi-hourly distribution of the decision index over the course of the day. By closer inspection, one can depict a somewhat bell-shaped pattern that is experienced throughout the day with the maximum values occurring between 11:00 and 13:00.

The associated CAI curve is depicted hourly in Fig. 9. The output functionality reveals that the highest CAI is

Table 1
Decision Index Values for 24 h

Hour	1	3	5	7	9	11	13	15	17	19	21	23
Decision index	0.225	0.210	0.225	0.801	0.883	0.889	0.889	0.585	0.237	0.210	0.448	0.338

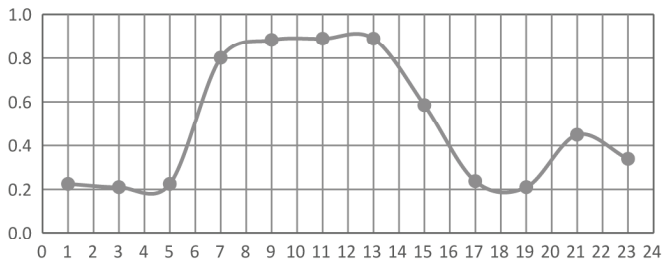

Figure 9. Customer acceptance index value versus time of day.

achieved in the middle of the day, particularly between the hours of 07:00 and 13:00. There is a gradual fall off of this as the typical workday comes to a close.

5. Conclusion

In this paper, a novel PIEV customer behaviour model is proposed employing fuzzy logic concepts. In order to investigate the effect of several factors on owner behaviour, a comprehensive questionnaire has been designed for data collection to gather enough historical data to model and analyse the preferences of the PIEV owners. This set of data has been deployed in the fuzzification process to express their behaviours qualitatively. Mamdani decision-making and rules were used to define a CAI based on four fuzzy inputs: cost of electricity (CE), cost of fuel (CF), fast/slow charging penetration (FSP), and controlled/uncontrolled charging penetration (CUP). Consequently, the proposed method produces a value in the [0,1] range. Obtained results demonstrate that there is an effective scenario of charging in the interval of [7,14] (07:00–14:00). This result shows that the customers tend to charge their PIEV during the day time. Furthermore, the surface views reveal a strong correlation between CE and CF. FSP and CUP also demonstrate a strong dependence on each other. This result shows that the correlation between factors comes from the nature of them since CE and CF are economic parameters but CUP and FSP depend on customers' decision.

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Biographies

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