MODELING VEHICLE CHOICES AND CHARGING BEHAVIOR OF PLUG-IN ELECTRIC VEHICLE OWNERS JOINTLY USING DYNAMIC DISCRETE CHOICE MODEL

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Plug-in Electric Vehicle (PEV) owners’ decisions on which vehicle to use for a travel day can be influenced by the expectation of the charging opportunities during the day. The charging decision at one stop can be influenced by the characteristics of future charging opportunities. The models of previous studies usually treat vehicle choices (which car to drive for the travel day) and charging choices of PEV owners as isolated decisions, which could cause underestimation of the demand for public charging facilities. This paper applies the dynamic discrete choice model (DDCM) with a finite horizon to jointly analyze vehicle choices and charging choices of PEV owners in a travel day based on stated preference data. The combination of Nested Fixed Point Algorithm and finite mixture solution based on EM algorithm proposed by Arcidiacono and Jones is utilized to capture the heterogeneity of decision-making among PEV users. The final model groups the PEV users into two classes: 63% in class 1 and 37% in class 2. The respondents in class 1 tend to pay significantly more money to avoid being stranded and would try to avoid using Battery Electric Vehicles (BEVs) when the public charging supply is not sufficient. In this group, the Plug-in Hybrid Electric Vehicle (PHEV) users tend to value the charging cost and gasoline cost similarly. The other group (class 2) of PEV users appears to be less cautious about being stranded and tends to use BEV more frequently for long distance trips than class 1. The PHEV owners in class 2 appear to try to avoid using gasoline because they value gasoline cost significantly more heavily than charging cost.

Key words: PEV, vehicle choice, charging behavior, stated preference data, DDCM
1 INTRODUCTION

The availability of public charging infrastructure intuitively appears to be a key enabler of Plug-in Electric Vehicle (PEV) adoption, increasing the operating radius of Battery-Electric Vehicles (BEVs), and increasing the fraction of electric powered miles in Plug-in Hybrid Electric Vehicles (PHEVs). However, data from the U.S. Department of Energy’s EV Project indicate that public charging does not have a high utilization rate so far: BEV drivers are recharging only once per day, on average—significantly less frequent than PHEV drivers—despite having no alternative power source besides electricity (1). The low utilization of public chargers does not necessarily mean the demand of public charging is low because it could be due to the lack of public charging opportunities. To mitigate the effect of the limited range of BEVs, a lot of BEV adopters may keep the choice of choosing an internal combustion engine vehicle (ICEV) for relatively long distance travel. When they observe the lack of public charging supply and the possibility of being stranded in the middle of the day, they could either choose to use their own ICEV/ PHEV or rent an ICEV vehicle (RENT) if they do not own one.

For a travel day that needs to be completed by driving, PEV owners usually face two stages of decisions as presented by Figure 1: whether to use PEV for the day (stage 1 decision), and if so, whether to charge the PEV at the stops as the day progresses (stage 2 decision). The decisions of the two stages are inseparable intuitively: the vehicle choice influences whether they will face the charging decisions later, and the expectation of future charging opportunities influences the vehicle choice. Modeling the stage 2 decisions of charging choices alone may lead to underestimation of charging demand. The charging decisions at any two stops in the travel day are not independent either: the charging decision at one stop influences whether the vehicle needs to be charged at the following stops, and the expectation of future charging opportunities influences the charging decision at the current stop. This dependence between an earlier decision and a later one could be translated into the following according to the utility theory: a decision at an earlier stop may affect not only the current utility, but the expected utility later of the following stops; the value of the expected future utility may affect the decision at the current stop.
Figure 1 Decision tree of PEV owners for a particular travel day

Previous literatures on the empirical models of charging choices mainly focus on static discrete choice models and treat charging choices as isolated decisions. The development of models on charging behavior of PEV users is shown by Table 1. Mixed logit model and multinomial model are the most common methods for analyzing charging behavior. Daina first developed a multinomial model to test the effect of PEV state of charge (SOC), trip purpose, trip distance and the characteristics of charging opportunities on the choice of the timing of charging (2). Then mixed logit model is then proved to be a more suitable approach to modeling PEV charging choices than multinomial logit model because it considers the heterogeneity (3, 4, 5). Latent class logit model captures heterogeneity by assigning the individuals to a finite number of classes based on socio-demographic characteristics. It is used to model the charging choices at isolated charging opportunities in several studies and is proved to provide better model fitness than mixed logit models and offers more elegant explanations of the results (7, 8, 9). Ge and MacKenzie applied a dynamic discrete choice model (DDCM) to analyze the charging choices of PHEV users at all the charging opportunities in a travel day based on stated preference data but it did not consider the stage 1 decision on vehicle choices (11).
### TABLE 1 Development of empirical literature on charging behavior of PEV users

<table>
<thead>
<tr>
<th>Authors</th>
<th>Output</th>
<th>Independent Variables</th>
<th>Data Source</th>
<th>Modeling Approach</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daina, N (2013)</td>
<td>Timing of charging</td>
<td>SOC, trip purpose, distance, dwell time</td>
<td>Stated preferences of UK car drivers (mostly non-PEV)</td>
<td>Multinomial logit</td>
<td>(2)</td>
</tr>
<tr>
<td>Zoepf, S., et al (2013)</td>
<td>Charge or not at the end of a trip</td>
<td>SOC, dwell time, day &amp; time, location, last trip</td>
<td>Instrumented pre-market Prius PHEVs in U.S.</td>
<td>Mixed logit</td>
<td>(3)</td>
</tr>
<tr>
<td>Jabeen, F., et al (2013)</td>
<td>Location and timing of charging</td>
<td>Price, location, duration, time of day</td>
<td>Stated preferences of Australian PEV owners</td>
<td>Mixed logit</td>
<td>(4)</td>
</tr>
<tr>
<td>Sun, X., et al (2015)</td>
<td>Timing of end-of-day charging</td>
<td>SOC, days until next trip, VMT next travel day, work day, night time, fast charging experience</td>
<td>Instrumented PEVs (120-180 km range) in Japan</td>
<td>Mixed logit</td>
<td>(5)</td>
</tr>
<tr>
<td>Sun, X., et al (2014)</td>
<td>SOC at start of mid-trip fast-charge events</td>
<td>Charging station density, region, battery size, daily trips &amp; VMT, speed, HVAC</td>
<td>Instrumented PEVs (120-180 km range) in Japan</td>
<td>Stochastic frontier modeling</td>
<td>(6)</td>
</tr>
<tr>
<td>Yu, H. and MacKenzie, D. (2016)</td>
<td>Charge or not at the end of a trip</td>
<td>Charge energy (the energy that could be taken on during a stop), day &amp; time, location, last trip</td>
<td>Instrumented pre-market Prius PHEVs in U.S.</td>
<td>Mixed logit and latent class logit</td>
<td>(7)</td>
</tr>
<tr>
<td>Wen, Y., et al (2016)</td>
<td>Charge or not at a public charging station</td>
<td>Recharging price at the station, electricity cost to get a full charge at home, dwell time, charging power</td>
<td>Stated preferences of U.S. BEV owners</td>
<td>Mixed logit and latent class logit</td>
<td>(8)</td>
</tr>
<tr>
<td>Ge, Y., et al (2016)</td>
<td>Charge or not at a public charging station</td>
<td>Recharging price at the station, electricity cost to get a full charge at home, dwell time, charging power, gasoline price</td>
<td>Stated preferences of U.S. PHEV owners</td>
<td>Latent class logit model</td>
<td>(9)</td>
</tr>
<tr>
<td>Daina, N. and Polak, J. (2016)</td>
<td>Duration between charging events</td>
<td>SOC, gender, age, range anxiety indicator, whether to use PEV to go to work/school</td>
<td>Instrumented Nissan Leaf vehicles and a questionnaire among the drivers</td>
<td>Hazard model</td>
<td>(10)</td>
</tr>
<tr>
<td>Ge, Y. and MacKenzie, D (2017)</td>
<td>Charge or not at all the charging opportunities of the whole travel day</td>
<td>Recharging price at the station, electricity cost to get a full charge at home, dwell time, charging power, gasoline price, availability of chargers</td>
<td>Stated preferences of U.S. PHEV owners</td>
<td>DDCM with observed heterogeneity</td>
<td>(11)</td>
</tr>
<tr>
<td>This paper</td>
<td>Whether to choose PEV for a particular travel day, and if so whether to charge the PEV at the charging opportunities as the day progress</td>
<td>Recharging price at the station, electricity cost to get a full charge at home, dwell time, charging power, gasoline price, availability of chargers</td>
<td>Stated preferences of U.S. PEV owners (including BEV and PHEV)</td>
<td>DDCM with unobserved heterogeneity</td>
<td>This paper</td>
</tr>
</tbody>
</table>
This paper applies DDCM to model the vehicle choice and charging choices jointly under the uncertainty of energy consumption and the uncertainty of availability of chargers with the consideration of unobserved heterogeneity. The fundamental principle in DDCM analysis is that choices in any period are assumed to be made in a dynamic programming framework such that the choices made will maximize the net present value of the current utility and expected future utility (12). A DDCM is more suitable when the utility of a decision maker’s choices depend on choices previously made, and when those earlier choices were made knowing that there would be uncertain future payoffs. At each time \( t \), decision-maker \( i \) with characteristics \( X_i \) observes the state variables \( s_{it} \) (e.g. the remaining range of the PEV) and chooses his action \( d_{it}^* \) (e.g. choose among BEV, PHEV, ICEV, and RENT; choose to charge or not) so as to maximize his expected net utility over the current period and all future periods, as shown in equation (1):

\[
d_{it}^*(s_{it}) = \arg\max_{d_{it} \in D_{it}} E_t \left[ \sum_{j=0}^{T-t} \beta^j U(s_{i,t+j}, d_{i,t+j}, X_i, \theta) \right]
\]

\( U(s_{i,t}, d_{i,t}, X_i, \theta) \) is the flow utility of decision-maker \( i \) at time period \( t \), which depends on the structural parameters \( \theta \) in addition to the choices \( d_{it} \) and states \( s_{it} \). \( E_t \) represents the function that calculates the expected value of the intertemporal payoff from period \( t \) to the final period \( T \). The earlier choices will influence the future utility because the current decision \( d_{it} \) influences the future state variables \( s_{i,t+1} \) via a process captured by the state transition probability \( F(s_{i,t+1}|s_{i,t}, d_{i,t}) \). The expected future opportunities influence the earlier choices through the expected utility value. Parameter \( \beta \) is a discount factor between 0 and 1, and the transition function represents the uncertainty of the future states (e.g. due to variability in in-use energy consumption and the uncertain availability of charging stations).

The analysis of this paper is based on the data from a web-based interactive survey where the respondents were firstly asked about their socio-demographic information and the specific information of vehicles they own, then presented with travel day scenarios characterized by planned distance and stops, gasoline price, charging price, charger level and availability of chargers. In each scenario, the respondents were first asked whether they would choose to use their PEV for this particular travel day based on the charging opportunities, then if so, whether to charge their PEV at each stop as the day progresses.

The outline of the paper is as follows. The section 2 describes the development of the online interactive survey tool and the survey management; data from the survey are then presented at section 3. The details on model framework, specification, and the estimation are in section 4. The results are then presented in section 5. The last section draws conclusions.

2 SURVEY
The survey consisted of two parts: (1) a questionnaire on socio-demographic information and vehicle ownership; and (2) a travel day simulation where the respondents were presented with travel days characterized by distance, charging opportunities and characteristics of charging opportunities such as charging price, level and availability of chargers.

2.1 Background Information

The questionnaire covered a variety of sociodemographic questions, including: age, gender, education, household income, household size and zip code of home address. The respondents were also asked to report the specific information of the vehicles: make, model, year, maximum and minimum full range of PEVs both for summer and winter respectively. Since this survey was conducted in summer, the average value of maximum summer full range ($r_{\text{max}}$) and minimum summer full range ($r_{\text{min}}$) is denoted as reported range ($r_{\text{reported}}$), which was used to customize the choice experiments of the survey.

$$r_{\text{reported}} = \frac{1}{2}(r_{\text{min}} + r_{\text{max}})$$

2.2 Travel Day Simulation

Each respondent was presented with eight scenarios featuring travel days that are characterized by the following variables: planned travel distances, charging price, charging power, dwell time, gasoline price and the availability of the chargers. The respondents were asked to choose the vehicles and make charging decisions if they choose their PEVs. Graphic display and experiment design of the scenarios are two key elements of the simulation design.

2.2.1 Display of the scenarios

In this section, each respondent was presented with 8 scenarios pre-designed by the researchers and customized according to the individuals’ EV ranges. Considering it is rather difficult to present the respondents with complex scenarios that are plausible to every one of them without collecting a large set of information on their daily travel, instead of asking the respondents to make decisions for themselves, we ask them to give advice for individuals that are very similar to them: with the same background information. Hsee and Weber (13) refer to this advisee as a “vivid other”. Porman (14) found that when people are making decisions for others, there is a bigger tendency to seek the ability to justify their choices, while when in their own decision making process, “people usually exhibit higher degrees of attribute prominence”. So at the beginning of the charging choice experiment part, the respondents will be first introduced to their vivid other (also called a digital avatar). As shown in figure 1.
Then in each scenario, the respondent was firstly presented with a specific travel day (Figure 2 screenshot 1), and then they were asked whether to choose a PEV that they own for this particular travel day, if so, whether to charge at each station with the day progress (Figure 2 screenshot 2-5). One noteworthy detail is that the information listed on the graph is displayed item by item using animation, which gives the respondents time to absorb the information. If the respondent chooses to use a PEV for the presented travel day, the survey tool will go through stop by stop and ask the respondent to make charging decisions. Interested readers could check this website for the survey tool.¹

¹ Link of the survey tool: http://test1.code-crew.co.uk/
FIGURE 2 Screenshot 1 of the survey tool: Display of Jane’s travel day
Jane's travel day
Scenario 5
Which car do you think Jane should choose?

2014 Nissan Leaf
Battery State of Charge: 100%
Remaining range: 60 mi

2015 Acura MDX 2WD
Gasoline price: $2.50

FIGURE 2 Screenshot 2 of the survey tool: vehicle choice for the travel day
FIGURE 2 Screenshot 3 of the survey tool: Charging decision of the first stop
FIGURE 2 Screenshot 4 of the survey tool: Charging decision of the second stop

FIGURE 2 Screenshot 5 of the survey tool: Indicate Jane made it home
2.2.2 Experiment design of the scenarios

A fractional factorial experimental design was used to generate the travel day scenarios and unrealistic scenarios (for example a travel day with negative planned travel distance) were deleted. Respondents were instructed to assume that other factors (such as the cost and availability of parking) would not be affected by the decision of whether or not to charge. The attributes and levels characterizing the choice situations are listed in TABLE 2.

**TABLE 2 Attributes and Their Levels of the Experiments**

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Variable</th>
<th>Description</th>
<th>Attribute levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Charging price ($/h)</td>
<td>( p_{\text{charging}} )</td>
<td>The recharging price at the station</td>
<td>$0.50/h; $1.00/h; $1.50/h; $2.00/h; $5.00/h</td>
</tr>
<tr>
<td>Charging power (kW)</td>
<td>( P_{\text{power}} )</td>
<td>The maximum charging speed at the station</td>
<td>1.9kW; 6.6kW</td>
</tr>
<tr>
<td>Dwell time (h)</td>
<td>( t_{\text{dwell}} )</td>
<td>The time duration for which the respondent will stay at this station</td>
<td>0.25h; 0.50h; 1h; 2h; 4h; 8h</td>
</tr>
<tr>
<td>Planned distance of the travel day (mi)</td>
<td>( L )</td>
<td>The distance of the whole travel day</td>
<td>Reported range - 40mi;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Reported range - 20mi;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Reported range - 10mi;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Reported range - 5mi;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Reported range;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Reported range - 10mi;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Reported range + 5mi;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Reported range + 10mi;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Reported range + 20mi;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Reported range + 40mi.</td>
</tr>
<tr>
<td>Gasoline price ($)</td>
<td>( p_{\text{gas}} )</td>
<td>Gasoline price</td>
<td>$2.50/gallon; $3.00/gallon; $3.50/gallon; $4.00/gallon; $4.50/gallon</td>
</tr>
<tr>
<td>Availability</td>
<td>( A% )</td>
<td>The chance that there is a plug available at a charging station</td>
<td>20%, available 1 out of 5 visits;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>40%, available 2 out of 5 visits;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>60%, available 3 out of 5 visits;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>80%, available 4 out of 5 visits;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>100%, always available.</td>
</tr>
</tbody>
</table>

Remaining range is the amount of electric range left for the PEV when respondent \( i \) arrives at one station \( i \). The survey tool calculates the remaining range at each station by estimating the energy consumption of each trip based on the vehicle specific information reported by the respondents. In real life, the range consumed of a certain distance of driving is uncertain due to driving habits, traffic condition and weather conditions, etc. This uncertainty of the range consumed \((r_{\text{consumed}})\) for distance \( l \) is considered by generating a random number according to the maximum and minimum range reported by the respondents, see equation (3).

\[
r_{\text{consumed}} = l + l \cdot \alpha \cdot \rho_{t}
\]  (3)
Random variable $\alpha$ is generated based on triangular distribution with maximum value of 1, minimum value of -1 and median value as 0. $\rho_i$ is defined as the uncertainty factor based on the reported maximum ($r_{\text{max}}$) and minimum summer ($r_{\text{min}}$) full range, as shown by equation (4).

$$\rho_i = \frac{r_{\text{max}} - r_{\text{min}}}{r_{\text{reported}}} \quad (4)$$

When the respondents do not own an ICEV, the option “rent a car” is presented to for the scenarios. The rental cost ($c_{\text{rental}}$) is a random value from $30 to $100.

3 DATA

The survey was conducted during June to July 2016. The respondents were recruited mostly through the Electric Auto Association (EAA) and Plug-in America, whose members are generally enthusiastic about electric vehicle technology and related research, and willing to participate into the survey without any extrinsic incentives. There were in total 1014 PEV respondents, 916 of whom completed the full survey. A descriptive analysis of the sample is shown in Table 2. 81% of the respondents were male. The reported household income among the respondents is higher than average, with around 44% of respondents reporting a household income over $140,000. More than 50% of the respondents have at least Bachelor’s degree. 878 of the respondents have BEVs and 276 own PHEVs. More than 54% of the respondents have BEV and ICEV, and 21% of the respondents just have BEV in their households.
**TABLE 3 Description of the Sample**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Category</th>
<th>Sample Frequency</th>
<th>Sample Percentage</th>
<th>Variable</th>
<th>Category</th>
<th>Sample Frequency</th>
<th>Sample Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>18-34</td>
<td>110</td>
<td>12%</td>
<td>&lt;$19,999</td>
<td></td>
<td>71</td>
<td>7%</td>
</tr>
<tr>
<td></td>
<td>35-45</td>
<td>203</td>
<td>22%</td>
<td>$20,000-$39,999</td>
<td>72</td>
<td>7%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>46-55</td>
<td>250</td>
<td>28%</td>
<td>$40,000-$59,999</td>
<td>96</td>
<td>9%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>55-65</td>
<td>152</td>
<td>17%</td>
<td>$60,000-$79,999</td>
<td>77</td>
<td>7%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>65+</td>
<td>194</td>
<td>21%</td>
<td>$80,000-$99,999</td>
<td>109</td>
<td>10%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Prefer not to answer</td>
<td>0</td>
<td>0%</td>
<td>$100,000-$119,999</td>
<td>93</td>
<td>9%</td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>Male</td>
<td>867</td>
<td>81%</td>
<td>$120,000-$139,999</td>
<td>70</td>
<td>7%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>190</td>
<td>18%</td>
<td>$140,000-$159,999</td>
<td>54</td>
<td>5%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Prefer not to answer</td>
<td>17</td>
<td>2%</td>
<td>$160,000-$179,999</td>
<td>231</td>
<td>22%</td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>Less than High School</td>
<td>39</td>
<td>4%</td>
<td>$180,000-$199,999</td>
<td>45</td>
<td>4%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>High School / GED</td>
<td>35</td>
<td>3%</td>
<td>&gt;$200,000</td>
<td>141</td>
<td>13%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Some College</td>
<td>120</td>
<td>11%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2-Year College Degree (Associates)</td>
<td>75</td>
<td>7%</td>
<td>BEV only</td>
<td>219</td>
<td>21%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>4-Year College Degree (BA, BS)</td>
<td>410</td>
<td>38%</td>
<td>PHEV only</td>
<td>68</td>
<td>6%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Master’s Degree</td>
<td>264</td>
<td>25%</td>
<td>BEV &amp; ICEV</td>
<td>570</td>
<td>54%</td>
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<tr>
<td></td>
<td>Doctoral Degree</td>
<td>126</td>
<td>12%</td>
<td>BEV &amp; PHEV</td>
<td>38</td>
<td>4%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Professional Degree (MD, JD)</td>
<td>5</td>
<td>0%</td>
<td>PHEV &amp; ICEV</td>
<td>119</td>
<td>11%</td>
<td></td>
</tr>
</tbody>
</table>

**4 MODEL**

**4.1 A Brief Literature Review On DDCM**

DDCM has been widely used in economic analysis and social science (15). It models choices based on intertemporal tradeoffs, which has obvious benefits for a lot of economic problems. For durable goods such as bus engines, DDCM considers the intertemporal trade-offs between the current replacement cost and future maintenance cost, which is one classic problem analyzed by Rust (16). For storable goods such as ketchup, it considers the intertemporal trade-offs between savings from a low price today and high storage cost in the future (17). DDCM problems are also broadly applied in some social science topics such as job search problem (18) and reproductive choices (19). In transportation area, there is not a lot of applications until recently partly due to
the massive computation cost (20). In 2013, Cirillo et al. used DDCM to analyze car ownership behavior with consideration of consumers’ expectations of future product characteristics (21).

The development of estimation methods of DDCM has a short history. Rust first developed Nested Fixed Point Algorithm (NFPA) for the estimation of a single agent dynamic model (16), which generates consistent estimates but suffers from a dimension curse: in general, DDCM with high dimensions of state variables are usually intractable by NFPA (22). Two-Step method that came out later has relatively lower computation cost because the value functions do not need to be calculated based on the state transition distributions but simulated based on the conditional choice probabilities (23). The model of this study utilizes NFPA because it is impossible to calculate conditional choice probabilities based on our data set: there is not enough repetitions of the same combination of state variables. NFPA is applicable in this case because most of our state variables are deterministic. We applied the finite mixture solution based on EM algorithm proposed by Arcidiacono and Jones to capture the heterogeneity of decision-making among PEV users (24). The details of the model set-up and estimation are explained in the following of this chapter.

4.2 Table Of Variables

Before we overwhelm you with a good amount of equations, the following table on the definitions and sources of the variables can be used as a reference list for the variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Variable name</th>
<th>Description</th>
<th>Source or Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_{max} / r_{min}$</td>
<td>Maximum/minimum range (mi)</td>
<td>The maximum/minimum summer full range of PEV</td>
<td>From the questionnaire</td>
</tr>
<tr>
<td>$p_{charging}$</td>
<td>Charging price ($/h$)</td>
<td>The recharging price at the station</td>
<td>Attribute of the experiment design</td>
</tr>
<tr>
<td>$Power$</td>
<td>Charging power (kW)</td>
<td>The maximum charging speed at the station</td>
<td>Attribute of the experiment design</td>
</tr>
<tr>
<td>$t_{dwell}$</td>
<td>Dwell time (h)</td>
<td>The time duration for which the respondent will stay at this station</td>
<td>Attribute of the experiment design</td>
</tr>
<tr>
<td>$L$</td>
<td>Planned distance of the travel day (mi)</td>
<td>The distance of the whole travel day for one scenario</td>
<td>Attribute of the experiment design</td>
</tr>
<tr>
<td>$p_{gas}$</td>
<td>Gasoline price</td>
<td>Gasoline price for one scenario</td>
<td>Attribute of the experiment design</td>
</tr>
<tr>
<td>$A%$</td>
<td>Availability rate (%)</td>
<td>The chance that there is a plug available at a charging station</td>
<td>Attribute of the experiment design</td>
</tr>
<tr>
<td>$c_{rental}$</td>
<td>Rental cost ($)</td>
<td>The cost of renting an ICEV</td>
<td>Attribute of the experiment design</td>
</tr>
<tr>
<td>$r_{reported}$</td>
<td>Reported range (mi)</td>
<td>The average value of maximum summer range and minimum summer range</td>
<td>Equation (2)</td>
</tr>
<tr>
<td>$r_{consumed}$</td>
<td>Range consumed (mi)</td>
<td>The range consumed for certain distance $l$.</td>
<td>Equation (3)</td>
</tr>
<tr>
<td>$\rho_i$</td>
<td>Uncertainty factor</td>
<td>Uncertainty factor of the PEV range</td>
<td>Equation (4)</td>
</tr>
<tr>
<td>$d_{it}$</td>
<td>Decision</td>
<td>Decision of respondent $i$ at stop $t$</td>
<td>Equation (5)</td>
</tr>
<tr>
<td>$s_{it}$</td>
<td>Vector of state variable</td>
<td>Vector of state variable of respondent</td>
<td>Equation (5)</td>
</tr>
</tbody>
</table>
The model jointly incorporates the two decision stages in every scenario: mode choice (the stage 1 model) and then charging choices (the stage 2 model). The survey data can be expressed as equation (5), in which \(i\) denotes the respondents, and \(t\) denotes the stops of individual \(i\). \(d_{it}\) is the decision of respondent \(i\) at period \(t\) (vehicle choice or charging decision at stop \(i\)). \(N\) is the number of respondents and \(T_i\) is the number of periods for respondent \(i\).

\[
Data = \{d_{it}, s_{it}, i: 1, 2 ... N; t: 1, 2, ..., T_i\}
\]  

At every stop \(t\), each individual chooses among \(J\) mutually exclusive alternatives to maximize the net utility, as in: \(d_{it} = \{j: jeD = \{1,2, ..., J\}\}\). The expression \(d_{it} = j\) means that the respondent \(i\) choose alternative \(j\) at period \(t\). Denote the choice indicator \(I\) as equation (6):

\[
I(d_{it} = j) = \begin{cases} 
1, & \text{if } d_{it} = j \\
0, & \text{if } d_{it} \neq j 
\end{cases}
\]  

For the stage 1 model, the choice set includes the four possible modes: BEV, PHEV, ICEV, and RENT. The choice set varies on the individual level. For stage 2 model, the choice set is the

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>(T_i)</td>
<td>Final decision period</td>
<td>(T_i) is the number of periods for respondent (i).</td>
</tr>
<tr>
<td>(I(d_{it} = j))</td>
<td>Choice indicator</td>
<td>Whether choice (j) was chosen by respondent (i) at stop (t).</td>
</tr>
<tr>
<td>(rr_{i,t})</td>
<td>Remaining range (mi)</td>
<td>Remaining range of the PEV of respondent (i) at stop (t).</td>
</tr>
<tr>
<td>(r_{obtained})</td>
<td>Range obtained (mi)</td>
<td>The range obtained after a stop.</td>
</tr>
<tr>
<td>(ECR)</td>
<td>Electricity consumption rate (kWh/mi)</td>
<td>Electricity consumption rate in charge-depleting mode.</td>
</tr>
<tr>
<td>(l_{it})</td>
<td>Distance from one stop to the next (mi)</td>
<td>Distance from station (t) to station (t+1) for respondent (i).</td>
</tr>
<tr>
<td>(a_{it})</td>
<td>Dummy variable: whether charger is available or not</td>
<td>Whether there is charger available at stop (t) for respondent (i).</td>
</tr>
<tr>
<td>(t_{plug_{i,t}})</td>
<td>Plug time (h)</td>
<td>The amount of time the PHEV stays plugged in to the EVSE.</td>
</tr>
<tr>
<td>(c_{charging_{i,t}})</td>
<td>Charging cost at the stop ($)</td>
<td>The total charging cost if an individual chooses to charge in the specified situation.</td>
</tr>
<tr>
<td>(S_{BEV} (S_{BEV_charge,i,t}, S_{BEV_not_charge,i,t}))</td>
<td>Stranded</td>
<td>(S_{BEV}) is a dummy variable showing whether the driver will be stranded on the way to the next charging opportunity. It varies according to charging decision.</td>
</tr>
<tr>
<td>(c_{gas_{i,t}} (c_{gas_charge}, c_{gas_not_charge}))</td>
<td>Gasoline cost for PHEV ($)</td>
<td>The cost of gasoline that will be used to get to the next charging opportunity. It differs according to charging decision.</td>
</tr>
<tr>
<td>(gas_cost_{icev})</td>
<td>The gasoline cost ($) for ICEV</td>
<td>The gasoline cost for the ICEV according to the...</td>
</tr>
</tbody>
</table>

\[\text{Equation (5)}\]  

\[\text{Equation (6)}\]  

\[\text{Equation (7)}\]  

\[\text{Equation (8)}\]  

\[\text{Equation (9)}\]  

\[\text{Equation (10)}\]  

\[\text{Equation (11)}\]  

\[\text{Equation (12)}\]  

\[\text{Equation (13)}\]  

\[\text{Equation (14)}\]  

\[\text{Equation (15)}\]  

\[\text{Equation (16)}\]  

\[\text{Equation (17)}\]
binary choice of charging or not. Denote $d_{it} = 1$ if the respondent chooses to charge, $d_{it} = 0$ if
chooses not to charge.

### 4.4 State Variables

Denote $s_{i,t}$ as the vector of state variables at the stop $t$ of respondent $i$. State variables refer
to factors that can influence the value of utility, and then influence the choices. The model here
is specified as a DDCM of a forward-looking economic agent with six state variables. Two of the
state variables model the beliefs of the individuals about the remaining range and the availability
of chargers of the future stations. Another four state variables are deterministic values of the
characteristics of the future charging opportunities. State transition functions capture the
uncertainty of the individuals about the future states, denoted as: $F_{is}(s_{i,t+1}|d_{it}, s_{i,t})$. It is the
cumulative distribution function of state variable $s_{i,t+1}$ based on the current remaining range $s_t$
and the decision at the current stop $d_{i,t}$. The following three sub-sections will explain the state
variables and their transition functions in detail.

#### 4.4.1 State variable of remaining range ($rr_{i,t}$)

The remaining range at station $t+1$ ($rr_{i,t+1}$) equals to the remaining range at station $t$ $rr_{i,t}$
plus the range obtained at the station $t$ ($r_{obtained_{i,t}}$), then subtract the range consumed on the way
to the next charging opportunity ($r_{consumed_{i,t}}$), as expressed by the following equation:

$$rr_{i,t+1} = rr_{i,t} + r_{obtained_{i,t}} - r_{consumed_{i,t}} \tag{7}$$

Range obtained is the maximum electric range increase the PEV can get at the station during the
specified dwell time if the owner chooses to charge, zero if the owner chooses not to charge. We
measure the potential energy that can be obtained from recharging as the range obtained at the
station ($r_{obtained_{i,t}}$). If the dwell time ($tdwelt$) is sufficient for the PHEV to reach a full charge
($t_{full}$), the range obtained is the difference between the full range and the remaining range
($r_{remaining_{i,t}}$). Otherwise, the range obtained depends on the charging power (Power) and dwell
time ($tdwelt$), see equation (8).

$$r_{obtained_{i,t}} = \begin{cases} 
\text{Min}\left\{\frac{\text{Power} \times tdwelt}{ECR}, r_{full} - rr_{i,t}\right\}, & \text{if } d_{it} = 1 \\
0, & \text{if } d_{it} = 0 
\end{cases} \tag{8}$$

(ECR: Electricity consumption rate in charge depleting mode)

The range consumed ($r_{consumed_{i,t}}$) for a certain distance is uncertain due to factors such as road
condition and traffic condition, which causes the uncertainty of the remaining range at the future
stations. The distribution $g(r_{consumed_{i,t}}|l_{i,t})$ models the PEV users’ belief of range consumed
for driving the distance from station $t$ to station $t+1$: $l_{i,t}$. The triangular distribution density can
be shown in the following graph:
The probability density function $g(r_{\text{consumed},i,t} \mid l_{i,t})$ can then be expressed as:

$$
g(r_{\text{consumed},i,t} \mid l_{i,t}, \rho_i) =
\begin{cases}
0, & r_{\text{consumed},i,t} < (1 - \rho_i)l_{i,t} \\
\frac{[r_{\text{consumed},i,t} - l_{i,t}(1 - \rho_i)]}{\rho_i^2 l_{i,t}^2}, & (1 - \rho_i)l_{i,t} < r_{\text{consumed},i,t} < l_{i,t} \\
\frac{1}{\rho_i l_{i,t}}, & r_{\text{consumed},i,t} = l_{i,t} \\
\frac{2[l_{i,t}(1 + \rho_i) - r_{\text{consumed},i,t}]}{\rho_i^2 l_{i,t}^2}, & l_{i,t} < r_{\text{consumed},i,t} < l_{i,t}(1 + \rho_i) \\
0, & r_{\text{consumed},i,t} > (1 + \rho_i)l_{i,t}
\end{cases}
$$

(9)

According to equations (7), the only uncertain component of the $r_{\text{r}_i,t+1}$ is range consumed $r_{\text{consumed},i,t}$. So the density function of the state variable remaining range $r_{\text{r}_i,t+1}$ is also a triangular distribution with the density function as shown by equation (10):

$$
f(r_{\text{r}_i,t+1} \mid d_{i,t}, s_{i,t}, l_{i,t}, \rho_i) =
\begin{cases}
0, & r_{\text{r}_t+1} < r_t + r_o - l(1 + \rho_i) \\
\frac{[r_{\text{r}_t+1} - r_t - r_o + l(1 + \rho_i)]}{\rho_i^2 l^2}, & r_t + r_o - l(1 + \rho_i) < r_{\text{r}_t+1} < r_t + r_o - l \\
\frac{1}{\rho_i l}, & r_{\text{r}_t+1} = r_t + r_o - l \\
\frac{[r_r + r_o - l(1 - \rho_i) - r_{\text{r}_t+1}]}{\rho_i^2 l^2}, & r_t + r_o - l < r_{\text{r}_t+1} < r_t + r_o - l(1 - \rho_i) \\
0, & r_{\text{r}_t+1} > r_t + r_o - l(1 - \rho_i)
\end{cases}
$$

(10)
Note: some subscripts are deleted to simplify the equation. \( r_{i,t+1} \) is \( r_{i,t+1} \); \( r_t \) is \( r_{i,t} \); \( r_o \) is \( r_{obtained,i,t} \); \( l \) is \( l_{i,t} \).

4.4.2 State variable of the availability of the chargers (\( a_{i,t} \))

There are five levels of the availability variables in the scenarios \( A\%\in\{20\%, 40\%, 60\%, 80\%, 100\%\} \), as shown in table 1. The distribution of the availability of the chargers at station \( t \) for respondent \( i \) is assumed to be Bernoulli distribution with the success probability of \( A\%_{i,t} \). So the density of the distribution of the availability at station \( t \) is:

\[
k(a_{i,t}) = \begin{cases} A\%_{i,t}, & a_{i,t} = 1 \\ 1 - A\%_{i,t}, & a_{i,t} = 0 \end{cases}
\]

Charger availability between the stations is assumed to be independent, which mean the value of \( a_{i,t+1} \) is independent of \( a_{i,t} \). So the transit function of availability could be expressed as equation (10).

\[
k(a_{i,t+1}|a_{i,t}) = k(a_{i,t+1}) = \begin{cases} A\%_{i,t+1}, & a_{i,t+1} = 1 \\ 1 - A\%_{i,t+1}, & a_{i,t+1} = 0 \end{cases}
\]

4.4.3 Other deterministic state variables

The deterministic state variables include the following variables: charging price, dwell time, gasoline price and charging power. Instead of using these state variables directly in the utility function, these variables were used to derive the following variables: charging cost \( c_{charging} \), stranded \( S_{BEV} \), and gasoline cost of PHEV \( c_{gasoline} \).

\((1)\) Charging cost

Plug time \( (t_{plug}) \) is the time duration that the PEV stays plugged on the charger. We assume that once a PEV is plugged in, it will remain plugged until it is fully charged or it is time for the driver to depart. So if the car cannot reach a full battery during the dwell time, plug time will be equal to the dwell time. Otherwise plug time is equal to the time needed for the PEV to become fully charged. It is calculated as equation (13).

\[
t_{plug,i,t} = \min\left\{t_{dwell,i,t}, \frac{(r_{reported_i} - r_{i,t}) \times ECR}{Power}\right\}
\]

Plug time is used to calculate the charging cost at the stop, which is defined as the total charging cost if an individual chooses to charge at this station:

\[
c_{charging,i,t} = p_{charging} \times t_{plug,i,t}
\]

\((2)\) Stranded \( S_{BEV} \)
\( S_{BEV} \) is a dummy variable showing whether the driver will be stranded on the way to the next charging opportunity. It can be calculated according to equation (15). This value varies according to the charging decision. If the respondents choose to charge, it can be written as \( S_{BEV,\text{charge},i,t} \). If the respondents choose not to charge, it can be written as \( S_{BEV,\text{not charge},i,t} \).

\[
S_{BEV,i,t} = \begin{cases} 
1, & \text{if } rr_{i,t+1} < 0 \\
0, & \text{if } rr_{i,t+1} \geq 0 
\end{cases}
\] (15)

(3) Gasoline cost of PHEV

The gasoline cost is calculated based on the remaining range and the distance to travel to the next station, see (16).

\[
c\text{gas}_{i,t} = \max(0, \frac{l_{i,t} - (rr_{i,t} + r_{\text{obtained},i,t})}{\text{mpg}} \times p_{\text{gas}})
\] (16)

Gasoline cost depends on the respondents’ charging decisions at the stop. If the respondents choose to charge, it can be written as \( c_{\text{gas, charge}} \). If the respondents choose not to charge, it can be written as \( c_{\text{gas, not charge}} \).

(4) Gasoline cost of ICEV

For ICEVs, the gasoline cost is calculated according to the fuel economy (mpg), the gasoline price \( p_{\text{gas}} \) of the scenario, and the planned distance \( L \) of the travel day.

\[
\text{gas cost}_{i,\text{icev}} = \frac{L}{\text{mpg}} \times p_{\text{gas}}
\] (17)

4.5 Flow Utility and Value Functions

4.5.1 Flow utility

Flow utility \( (u(s_{i,t})) \) means the utility at one station based on the state variables, as in the one-period payoff. The flow utilities of the two-stage models are defined separately.

Stage 1 model (vehicle choice):

The utility of ICEVs is as shown by equation (18); for the choice of “rent a car”, the coefficients of rental cost and gasoline cost are estimated, as shown in equation (19); for BEV and PHEV, the alternative specific constant \( (\text{ASC}_{bev} \text{ and } \text{ASC}_{phev}) \) are estimated, as shown in equation (20) and equation (21).

\[
u_{i,\text{icev}} = \theta_1 \times \text{gas cost}_{i,\text{icev}} \] (18)
The flow utility of BEV and PHEV at this stage only include alternative specific constants might appear odd to some readers, but this is a reasonable specification because when the respondents decide whether to use their PEV for the travel day, they mainly consider the expected utility of charging in the future stops, which will be reflected by the stage 2 model specification.

**Stage 2 model** (charging choices):

For the charging choices of BEVs, the coefficients of charging cost and stranded are estimated, as shown by equation (22) and equation (23).

\[
U_{\text{bev charge},i,t} = \theta_4 * C_{\text{charging,bev},t} + \theta_5 * S_{\text{BEV charge},i,t} + \text{ASC}_{\text{bev,charge}}
\]

\[
u_{\text{bev,not charge},i,t} = \theta_5 * S_{\text{BEV not charge},i,t}
\]

For the charging choices of PHEVs, the coefficients of charging cost and gasoline cost are estimated, as shown by equation (24) and equation (25).

\[
u_{\text{phev,charge},i,t} = \theta_6 * C_{\text{charging, phev},t} + \theta_7 * c_{\text{gas,charge},i,t} + \text{ASC}_{\text{PHEV,charge}} \]

\[
u_{\text{phev,not charge},i,t} = \theta_7 * c_{\text{gas,not charge},i,t}
\]

### 4.5.2 Value functions

The intertemporal payoff function based on current and expected future utility is defined as value function \(V_{it}\) (equation (26)).

\[
V_{it}(s_{it}) = E_t \left[ \sum_{j=0}^{T-t} \beta^j U(s_{it+j}, d_{it+j}, \theta) \right]
\]

At each period \(t\), the decision made at station \(t\) will make respondent \(i\) achieve the biggest expected utility, as shown in equation (27). The optimal choice can also be defined as \(d_{ijt}^* \equiv 1\{d_{it}^*(s_{it}) = j\} .\)
\[ d_{it}^* (s_{it}) = \arg\max_{d_{it} \in D} V_{it}(s_{it}) = \arg\max_{d_{it} \in D} E_t \left[ \sum_{j=0}^{T-t} \beta^j u(s_{it+j}, d_{it+j}, X_t) \right] \] (27)

According to Bellman’s curve of optimality, the value function of respondent \( i \) at period \( t \) can be rewritten as equation (28).

\[ V_{it}(s_{it}) = \max_{j \in D} \left( u_{itj}(s_{it}) + \varepsilon_{itj} + \beta \int V_{it+1}(s_{it+1}) dF_{is}(s_{it+1} | d_{it}, s_{it}) \right) \] (28)

Define the conditional value function of respondent \( i \) at period \( t \) as the choice specific value function of alternative \( j \) denoted by \( v_{itj}(s_{it}) \). It can be calculated according to equation (29).

\[ v_{itj}(s_{it}) = u_{itj}(s_{it}) + \beta \int V_{it+1}(s_{it+1}) dF_{is}(s_{it+1} | j, s_{it}) \]
\[ = u_{itj}(s_{it}) + \beta \ln \sum_{k \in \mathcal{J}} \exp \{ v_{it+1j}(s_{it+1}) \} dF_{is}(s_{it+1} | j, s_{it}) \] (29)

According to random utility theory, the individual \( i \) chooses choice \( j \) in period \( t \) if and only if:

\[ v_{itj}(s_{it}) + \varepsilon_{itj} \geq v_{itk}(s_{it}) + \varepsilon_{itk} \quad \forall k \neq j \] (30)

### 4.6 Unobserved Heterogeneity And The Likelihood Function

To capture the heterogeneity of charging decision making among the PEV drivers, latent class framework is adopted into DDCM framework. Latent class models assume that all individuals can be separated into a finite set of classes (\( Q \) classes) and estimate structural parameters for each class. Here, taste heterogeneity is captured by allocating respondents to different classes in a probabilistic manner, allowing the probability of class membership based on the choices made.

The probability of choosing choice \( j \) under the condition that respondent \( i \) belongs to class \( q \) can be described by a conditional logit:

\[ p_{it}(d_{it} = j \mid \text{class } q) = \frac{e^{v_{ijt}(s_{it})}}{\sum_{h \in \mathcal{D}} e^{v_{ihjt}(s_{it})}} \] (31)

Denote the probability of respondent \( i \) belongs to class \( q \) as \( \pi_{i,q} \), then the probability of the alternative \( j \) being chosen for the respondent \( i \) at period \( t \) is:

\[ p_{it}(d_{it} = j) = \sum_{q=1}^{Q} \pi_{i,q} \cdot \frac{e^{v_{ijt}(s_{it})}}{\sum_{h \in \mathcal{D}} e^{v_{ihjt}(s_{it})}} \] (32)

The population probability of class \( q \) is defined as equation (33):
The probability of respondent $i$ being in class $q$, $\pi_{iq}$, can be calculated as the posterior probability based on the vehicle choice and charging decisions $d_{it}$ see equation (34).

$$\pi_{iq} = p(\text{class } q|d_{it}) = \frac{p(\text{class } q, d_{it})}{p(d_{it})}$$

$$= \frac{\pi_q \left[ \prod_{t=1}^{T} \prod_{j=1}^{J} \Pr(d_{it} = j|\text{class } q) l(d_{it}=j) \right]}{\sum_{q=1}^{Q} \pi_q \left[ \prod_{j=1}^{J} \prod_{t=1}^{T} \Pr(d_{it} = j|\text{class } q) l(d_{it}=j) \right]} \tag{34}$$

The log-likelihood can be calculated according to equation (35).

$$l_l(\theta) = \sum_{t=1}^{T} \sum_{j=1}^{J} \ln[p_{it}(d_{it} = j)] l(d_{it}=j)$$

$$= \sum_{t=1}^{T} \sum_{j=1}^{J} \left[ \sum_{q=1}^{Q} \pi_{iq} \frac{e^{v_{ijt}(s_{it})}}{\sum_{h\in D} e^{v_{ih}(s_{it})}} \right] l(d_{it}=j) \tag{35}$$

The log-likelihood of the sample can be calculated according to equation (36).

$$LL_N(\theta) = \sum_{i=1}^{N} l_l(\theta) \tag{36}$$

### 4.7 Model Estimation Using EM algorithm

The structural variables to be estimated for each class include the following:

$$\theta = \{\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7, \text{ASC}_{BEV\_charge}, \text{ASC}_{PHEV\_charge}, \text{ASC}_{BEV}, \text{ASC}_{PHEV}\}$$

The population probabilities of classes to be estimated are:

$$\pi = \{\pi_1, \pi_2, \ldots, \pi_Q\}.$$
For finite horizon problem like this, the decision in the last period $T$ is static, so the conditional value function at $T$ is the utility function, which means:

$$v_{iT}(s_{iT}, \text{class } q) = u_{iT}(s_{iT})$$  \hspace{1cm} (37)

Then the value function of all the earlier periods can be obtained through backwards recursion. For example, the conditional value function at $T - 1$ is then:

$$v_{i,T-1,j}(s_{i,T-1}, q) = u_{i,T-1,j}(s_{i,T-1}) + \beta \int \ln \sum_{h \in D} \exp\{v_{iT}(s_{iT}, q)\} \, dF_{is}(s_{iT}|j, s_{i,T-1})$$  \hspace{1cm} (38)

**Step 3: Update Posteriors of class probability**

The posterior probability of respondent $i$ in class $q$ is calculated according to equation (39):

$$\pi_{iq} = p(\text{class } q|d_{it}) = \frac{p(\text{class } q, d_{it})}{p(d_{it})} = \frac{\pi_q \left[ \prod_{t=1}^{T}(\Pr(d_{it} = j|\text{class } q))^{I(d_{it}=j)} \right]}{\sum_{q=1}^{Q} \pi_q \left[ \prod_{t=1}^{T}(\Pr(d_{it} = j|\text{class } q))^{I(d_{it}=j)} \right]}$$  \hspace{1cm} (39)

**Step 4: Update the population probabilities**

The population probability of class $q$ can be updated according to equation (40):

$$\pi_q = \frac{\sum_{i=1}^{N} \pi_{iq}}{N}$$  \hspace{1cm} (40)

**Step 5: Maximization of the likelihood function**

$$\theta^2 = \arg\max_{\theta} \sum_{i=1}^{N} \sum_{t=1}^{T_i} \sum_{q=1}^{Q} \pi_{iq} \cdot \ln \left[ \frac{e^{v_{ijt}(s_{it}, q)}}{\sum_{h \in D} e^{v_{ih,t}(s_{it}, q)}} \right]^{I(d_{it}=j)}$$  \hspace{1cm} (41)

**Step 6: Repeat step 2- step 6 until all the parameters converge.**

### 4.8 Bootstrap For Standard Errors

The standard errors based on the hessian matrix of maximization function (41) are biased downward because the value functions are treated as data in the maximization, but they are calculated based on the value of the parameters. So in this analysis, we used bootstrap with 250 simulated samples to calculate the standard errors.

### 5 RESULTS

The dynamic model with unobserved heterogeneity identified two types of PEV users with different behavioral patterns. One group that is more cautious about being stranded and
practical about the money they spend (class 1, 67%). The BEV owners in this group would pay
15 times more than the charging cost to avoid being stranded, which shows they have strong
range anxiety: the fear of being stranded in the middle of a trip because the battery of the BEV is
depleted (26). The PHEV owners in this class would try to minimize the total cost because they
value charging cost and gasoline cost quite similarly according to the scale of the coefficients.
The other group is less cautious about being stranded and tends to avoid using gasoline (class 2,
37%). The BEV owners in this class would pay 8 times more than the charging cost to avoid
being stranded, which shows less gas anxiety than class 1. PHEV owners in this class would pay
3 times more on average to avoid using gasoline according to the coefficients, which shows that
they have gas anxiety: the tendency to avoid using gasoline (9).

The classification of the respondents is not significantly associated with any socio-
demographic variables that we collected, which shows the different charging patterns are due to
some unavailable characteristics.

### TABLE 5: results of the DDCM for vehicle choice and charging choice

<table>
<thead>
<tr>
<th></th>
<th>class 1</th>
<th>p-value</th>
<th>class 2</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASC-BEV</td>
<td>2.567</td>
<td>0.04</td>
<td>1.193</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>ASC-PHEV</td>
<td>3.526</td>
<td>0.03</td>
<td>0.618</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>ASC-BEV charge</td>
<td>0.970</td>
<td>0.01</td>
<td>1.340</td>
<td>0.05</td>
</tr>
<tr>
<td>ASC-PHEV charge</td>
<td>0.340</td>
<td>0.06</td>
<td>0.420</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>$\theta_1$ (gas cost-ICEV)($)</td>
<td>0.070</td>
<td>0.24</td>
<td>0.154</td>
<td>0.01</td>
</tr>
<tr>
<td>$\theta_2$ (rental cost-RENT) ($)</td>
<td>-0.011</td>
<td>0.08</td>
<td>-0.030</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>$\theta_3$ (gas price*distance-RENT)($*mile)</td>
<td>0.00004</td>
<td>0.39</td>
<td>0.003</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>$\theta_4$ (charging cost-BEV)($)</td>
<td>-0.082</td>
<td>&lt;0.01</td>
<td>-0.323</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>$\theta_5$ (stranded)(0,1)</td>
<td>-1.311</td>
<td>&lt;0.01</td>
<td>-3.155</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>$\theta_6$ (gas cost-PHEV)($)</td>
<td>-0.628</td>
<td>&lt;0.01</td>
<td>-0.190</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>$\theta_7$ (charging cost-PHEV)($)</td>
<td>-0.851</td>
<td>&lt;0.01</td>
<td>-0.048</td>
<td>0.20</td>
</tr>
<tr>
<td>Membership Probability</td>
<td>63%</td>
<td></td>
<td>37%</td>
<td></td>
</tr>
<tr>
<td>Likelihood</td>
<td>-7889</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### 6 CONCLUSIONS

The current literature models vehicle choice and charging behavior at each station as
isolated decisions, which could cause underestimation of the demand of public charging facilities.
This paper uses DDCM with a finite horizon to model vehicle choice and charging choices in
one travel day jointly with consideration of heterogeneity of the PEV owners. The final model
classified the PEV users into two groups. Class 1 pays significantly more to avoid being stranded
and would try to avoid using BEV when the public charging system is not sufficient. In this
group the PHEV users tend to value the charging cost and gasoline cost similarly. The other
group (class 2) of PEV owners tends to be less cautious about being stranded and tend to use BEV more frequently for long distance trips than the other group. The PHEV owners in this group appear to try to avoid using gasoline because they value gasoline cost significantly more heavily. Respondents in class 2 are more likely to be the advocates of PEVs.

ACKNOWLEDGEMENTS

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References

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