Home EV Charging as a Commercial Service: A Mobile Application Approach Using Dynamic Pricing with a Markov Location Algorithm

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Abstract

The research introduces an alternative mobile application, ChargeBnB, employing an escort evolutionary game dynamic pricing algorithm and a Markov chain-based stochastic model for location determination. The pricing algorithm optimizes charging prices for EV and EVSE owners based on profit motives and externalities. Data gathered from surveys of 25 Households and drivers, including behavior and appliance usage, refines the algorithms. A case study demonstrates user experience, and the paper outlines the application's future overview. The proposed solution, combining dynamic pricing and strategic location determination, contributes to efficient EV charging resource allocation, increased revenue for EVSE owners

1 Introduction

In response to the growing environmental concerns associated with fossil fuels, various companies have increasingly introduced electric vehicles (EVs) to the market. EVs have emerged as a sustainable alternative to traditional fossil fuel cars, primarily due to their potential to reduce greenhouse gas emissions. EVs charging stations (CS) are increasing fast, however, in metropolitan cities such as New York City, there are limitations for CS due its infrastructure, however, in this paper we are aiming to offer a possible solution to this problem.

This project intends to develop the idea of shared home charging, specifically on enabling electric vehicle owners to find and use CS offered by homeowners, who open their home chargers for EVs that need a CS and explore the challenges and feasibility of implementing a home charging system for EV users. Our study presents a case study that showcases how our idea is implemented in a mobile application design on Figma. We gather user's information through a brief survey on the app and implement two algorithms from their answers: pricing and location. The pricing algorithm will let the EV owner see locations in the mobile application where home chargers are available alongside their costs and reviews. In the other hand, the location algorithm will let users register as a home charger facility and allow them to make profit out of their charger by letting other EV users utilize the charger in the times the homeowner sets.

2 Literature Review

Incentivizing EV owners to charge at specific locations and times presents a significant challenge that numerous entities, ranging from researchers [1][2] to governmental organizations, have sought to address. This includes initiatives such as the Biden-Harris EV Charging Action Plan [3] and Governor Hochul's charging discount program [4].

Our mobile application provides a platform for electric vehicle (EV) owners to find and use residential charging stations. Thus, the various methods of encouraging charging has been investigated. One such method, pricing, is analyzed in the next section.

Through our literature review, it has been determined that price-based incentives, which encompass various models can be categorized into two main groups: 1) types of pricing incentives, and 2) price determination. Our objective was to determine the best incentive structure, and price determination methodology for our application.

Pricing Incentive Structure:

The time of use (TOU) model is one approach where [5] explores the development of a dynamic TOU pricing strategy, focusing on user satisfaction. This strategy considers user travel and charging patterns to devise a TOU strategy tailored to a specific location. However, the analysis incorporates EV owner needs on an aggregate level, without providing any individual user specificity. In addition, demand response programs, as discussed in [6], propose the use of EV battery switching to further reduce the overall community load. Additionally, subscription models, offered by companies like EVCS, are another option, but is most beneficial for large scale EVSE owners. Finally, dynamic pricing models that account for variables such as grid supply and demand constraints are examined in [7][8].

Upon review of the current state of technology discussed above, we chose to use dynamic pricing for the ChargeBnB pricing structure. This structure mirrors models seen in public applications like Airbnb and Uber. Once the structure was decided, a price determination methodology based on the selected incentive structure was selected based on the discussion below.

Price Determination:

Dynamic pricing models can vary widely and include formulating the pricing challenge as a Markov Decision Problem and presenting several solutions such as Q-learning and actor-critic as proposed in [9]. However, this model requires there to be a known state transition probability, an externality such as competitor pricing was not considered. The authors of [10] propose an approach that optimizes the EVSE owners profit based on the reduction of the owner’s peak load. This benefits the EVSE owner but does not incentivize EV owners to charge. Escort evolutionary game theory is proposed in [11] using the algorithm to adjust prices based on the needs of EV owners and the system owner through an aggregator. While this model does not specifically use charging price to incentivize charging, the dynamic and customizability provide the best option for the ChargeBnB platform.

After evaluating the current state of technology as outlined above, we have chosen to implement the dynamic pricing model based on the escort evolutionary game dynamics detailed in [11]. This model provides a flexible method to establish the optimal price for EV and EVSE owners based on their profit and savings motives as well as individual externalities. Additionally, this model excels when empirical data can be used to augment the escort functions. Thus adjusting strategy performance to allow for tailored pricing, which improves in accuracy as it incorporates increasing amounts of usage data over time.

Data Acquisition:

To be able to effectively schedule the charging of vehicles, it is important to understand the energy consumption of the homeowner. [14] developed a representative schedule only for HVAC appliances for future diagnostics. [18] as well, only considered HVAC systems and assumed that an aggregator collects the required information on energy consumption and these systems were the main factors in understanding overall energy demand for planning EV infrastructure.

It is important to consider different factors when scheduling EVs to a charging station, in our case, to a home charger. Reference [15] highlights the necessity of situating charging stations in areas with ample parking by analyzing houses and EVs dimensions. According to [16], installing Level 2 chargers in private and residential spaces is advised to reduce the complexity and need for utility company approval for fast charging stations, which could deter homeowners. The "EV Project," a study cited in [13], investigated the driving and charging habits of Nissan LEAF drivers in 2012, revealing that most charging typically occurs when the EV's State of Charge (SoC) is between 50% to 60%. However, this data was collected with a public database. Conversely, [12] analyzed EV charging patterns using the 2017 National Household Travel Survey (NHTS) data, finding that charging usually starts at 41%, primarily when the SoC is between 40% to 50%. This study also noted that the average SoC at workplace and public charging stations is 47.8% and 39.1%, respectively. [17] observed a preference among drivers for charging stations on local streets rather than highways when SoC is low, emphasizing the importance of strategically placing stations in suburban areas.

The above-mentioned literature reveals that there are not enough factors taking place in the scheduling system of EVs to a charging station. It is important to increase the number of appliances for host homes when opening their chargers. None of the works mentioned in this literature review consider a vast number of appliances, nor gathered exact home energy consumption data, nor gathered personalized data to accommodate users. In the other hand some of the works mentioned helped us to concretely gathered the necessary data for the algorithms presented in this paper such as, [15] that emphasized the significance of focusing on suburban regions for developing residential charging models, particularly in areas with higher income levels. Specifically, the study highlighted the need to target homes that have both parking spaces and charging facilities.

Based on these discoveries, for our acquired data we decided to:

1. Survey several participants to accommodate based on homeowner preferences.
2. Consider a vast number of appliances based on participants answers.
3. It is necessary to consider electricity rates into our scheduling systems according to homeowners' electricity bill.
4. Study areas with a higher income. In our analysis, areas like Riverdale in The Bronx, characterized by an average household income of approximately $126,300 and a median income of $79,708, were particularly relevant for our research [19].
5. Consider market prices of charging stations in selected areas to base homeowner's charger rates on this.

Location Determination:

For a homeowner to utilize the ChargeBNB service as a source of income, they must consider their home's availability for charging. Two important factors to be examined in this decision include their lifestyle/personal schedule and their home energy consumption patterns to avoid problems such as obstructing their personal routine, as well as causing stress to their electrical system. Many approaches have been studied when it comes to the scheduling problem of household appliances with the ultimate goal of reducing energy consumption at peak grid times for users. Fuzzy Logic Controller methods for home energy management continue to grow in popularity as they facilitate the consideration of user comfort and the EV's SoC for future needs [25]. For systems with already implemented variable renewable energy, other ideas for the future suggest Utility Controlled Charging (UCC), where charging of EV's only occurs during times of excess renewable energy [23]. These proposals, however, exclude the possibility of user participation without the incorporation of smart devices in their home.

Less intrusive methods, like recommendation algorithms that suggest when and where to charge EVs are now in the conversation for the use of energy in a more efficient manner. Chained recommendations based on classification levels combat the frequency of congestion when arriving at charging stations for EV drivers and help the distribution of EVs amongst stations during such events [24]. Taking the grid into consideration, with the rise of EV usage, optimization problems for EV charging stations to shave peak loads are also explored [21]. These methods address energy efficiency from the perspective of charging stations that work on different schedules than a homeowner might. For that reason, recommendations that are more geared towards home charging applications are in the best interest of ChargeBNB, since users that are more informed about their energy consumption, as well as off-peak and on-peak hours, tend to make better decisions about their time of charging [26].

Markov's Chain-based stochastic model approach proposed in [27] resolves some of the concerns expressed above. Using only user's activity pattern, this algorithm predicts the likelihood of a household being in a specific 'energy state' (ranked from least active to most active), based on their previous state. These Markov methodologies can be used in conjunction with publicly available data and weather-related factors to predict household consumption [22]. This is not the only way, however, to obtain the inputs needed for this algorithm. Allowing users to be surveyed reduces the need for every participant of ChargeBNB to own a smart meter to understand their energy behavior. While [27] goes as far as calculating and predicting the energy consumption in kWh of the household, the probability of being in an energy state is sufficient for the purposes of this application. For this reason, this paper explores the implementation of a Markov chain-based stochastic model for the suggestion of a 'best-time' for a home to be available for charging, based on empirical data collected from user describing their energy usage and allowing them to input their available times to address user comfort.

3 Methodology

3.1 Overview

ChargeBnB introduces an innovative approach aimed at enhancing the accessibility of charging stations for electric vehicle (EV) drivers, augmenting revenue opportunities for homeowners who invest in Electric Vehicle Supply Equipment (EVSE), and enabling more effective distribution of electrical loads from EV charging across the grid. This is achieved by developing a mobile application, to meet the needs of both EV and EVSE owners, enabling them to efficiently negotiate charging arrangements.

The research paper details the essential features of the mobile application, underscoring its role in validating the viability and effectiveness of our novel approach to allocating EV charging resources. Key functionalities of the application include:

1. The application of an escort evolutionary game dynamic pricing algorithm, which plays a pivotal role in determining a mutually acceptable charging price for both parties involved.
2. A Markov chain-based stochastic model is used to determine the location, ensuring that EV owners are presented with privately-owned charging stations in proximity to them, in line with the availability and scheduling preferences of the EVSE owners.
3. To refine the parameters of these algorithms, the study leverages empirical data collected from surveys. Additionally appliance information and EV SoC data was collected.

After a description of the methods and data we present a case study demonstrating the user experience (UX) and flow of application for both the EV owner and the EVSE owner. Finally, the location, pricing, and data analysis from the case study are discussed.

3.2 Price Determination

Escort Evolutionary Game Dynamics

Escort evolutionary game dynamics (EEGD) is a modified approach to the standard evolutionary game dynamic algorithm. EEGD models the evolution of strategies within populations. Interactions within populations using each strategy causes evolutions as the proportion of the population using a strategy shift with each interaction. EEGD extends this process by using escort functions to adjust the influence of different strategies based on external factors or conditions. This enables more real-world modeling based on available data. The standard EEDG function, which demonstrates the rate of change of the population proportion using strategy k can be seen below in equation 1.

$$\dot{x}_k = \varphi_k(x_k)(f_k(\boldsymbol{x}) - \bar{f}\varphi(\boldsymbol{x}) \qquad eq. 1$$

Where:

- x_k is element k of the state vector of portions of the population following pure strategy, k.
- $\varphi_k(x_k)$ is the escort function associated with strategy k, which modulates the growth rate based on the strategy's performance.
- $f_k(x_k)$ is the payoff function for strategy k, which determines the benefit of playing strategy k given the current state x.
- $\bar{f}\varphi(x_k)$ is the weighted average payoff across all strategies, weighted by the escort function.

Using EEGD our methodology includes novel algorithms for determining the EV charging price. This is the contractual price agreed upon by both the EVSE owner and the EV owner with which to charge the vehicle where the payoff for each population group does not go below zero. In addition, external factors such as local market prices, ratings, and distance to the charging station are used to augment the payoff to determine a more accurate price.

The escort evolutionary game dynamic (EEGD) is designed using the methodologies described in [1]. The algorithm is modified so that the payoff function is instead the charge price from the perspective of the buyer and seller. Equilibrium is reached when the rate of change of the population proportions is less than 1%. The escort functions were determined using a trendline based on the empirical data. The data used was gathered from our surveys which are discussed in Section 3.4.

State Vector

The state vector (eq, 2) for EV owners is a vector indicating the proportion of the population following strategy k. Therefore, there are k elements in the vector, and the sum of the elements must equal to 1. A similar vector, y, is used for EVSE owners. In our model, there are 2 population groups which must have their strategies converge in the EEGD: 1. The EV owners who want to charge at lowest possible price, and 2. The EVSE owners, who want to sell at the highest possible price. Each strategy in the algorithm is a distinct price at which charging will occur. Each element in the state vector, x, represents the portion of the population using strategy (price) k. The initial state vector is set manually to start the evolutions. Each evolution changes the proportion of the population, x_k, using each strategy by $\dot{x}_k + \Delta t, where\ \Delta t = 1$.

The number of strategies is determined by the range of prices being considered for EV charging. These prices are constrained within the bounds of p_{max} and p_{min} described in below in equations 3 and 4.

$$x = [x_1, x_2, \dots, x_K]^T \qquad eq. 2$$

$$p\_min = max\{p_c \geq C, \hat{p} * .7\} \qquad eq. 3$$

$$p\_\max = min\,\{\hat{p} * 1.3, \frac{V}{E}) \qquad eq. 4$$

Where:

- p̂ is the average market price of charging at public charging stations in the surrounding area ($/kWh). The adjustments applied (.7, and 1.3) are to encompass the range of charging station prices.
- V is the maximum value the EV owner assigns to a fully charged vehicle ($)
- E is the energy required to fully charge the vehicle (kWh)

Payoff Function

The payoff functions (eq. 4-5) are used to determine the fit of each strategy. The payoff for the EV owner (f_k) demonstrates that their price maximum is based on the total utility that they gain from having a fully charged vehicle. This utility decreases as the price they must pay increases.

For EVSE owners the payoff function (g_k) represents the profit they make. Profit increase with the price, but this is not infinite. When the price is above what EV owners are willing to accept, no profit is made.

$$f_k(x) = V - p_b \cdot E \qquad eq. 5$$

$$g_k(y) = (p_c - C) \cdot E \qquad eq. 6$$

Where:

- p_c = the price EV charger owners want to charge ($/kWh)
- p_b = the price at which EV owners will buy ($/kWh)
- k = the strategy used (each discrete price, p_c and p_b)
- V = maximum value the EV owner assigns to a fully charged vehicle ($)
- E = the energy required to fully charge the vehicle (kWh)
- C = the cost of providing the charging service ($/kWh)

Escort Function

The escort function used to adjust the payoff growth rate of the EV owner's strategies was created by curve fitting the empirical data gathered in the surveys.

The distance that the EV owner must travel to the EVSE requires a specific escort adjustment (TABLE 1) as users adjust their utility for charging based on the inconvenience.

The escort function used to adjust the payoff growth rate of the EVSE owner's strategies was created by using the rating of the EVSE owner versus the average rating of the surrounding chargers. The empirical data indicated that the charging station rating mattered to users. However, no equation could be curve fit. Therefore, the simplified equation (eq. 8) seen below was used for all strategies greater than $\hat{p}$.

TABLE 1: ESCORT FUNCTIONS PER TIME TO CHARGER

Time (min)	Discounts (%)				Escort Functions y = φ_k
	5%	10%	15%	20%	
0	0.462	0.308	0.154	0.038	y = 1.3054e^(-16.3x)
1	0.577	0.308	0.154	0.038	y =-0.085ln(x) - 0.1573
2	0.077	0.077	0.077	0.038	y = -0.021ln(x)+0.0211
3	0.038	0.077	0.038	0.000	y = -0.025ln(x) - 0.0157
5	0.154	0.231	0.154	0.192	y = 0.0769x + .1731
6	0.038	0.038	0.000	0.000	y = -0.032ln(x) - 0.0507
7	0.000	0.000	0.000	0.038	y = 0.021ln(x) + 0.0558
7.5	0.000	0.000	0.038	0.038	y = 0.0318ln(x) + 0.0892
8	0.000	0.038	0.000	0.000	y = -0.004ln(x) + 0.0017
10	0.077	0.192	0.308	0.308	y = 0.1799ln(x) + 0.6171
15	0.038	0.000	0.231	0.192	y = 0.1415ln(x) + 0.4269
20	0.000	0.000	0.000	0.115	y = 0.063ln(x) + 0.1675
30	0.000	0.038	0.000	0.038	y = 0.0174ln(x) + 0.0575

Where:

- y is the population adjustment based on the time and discounts.
- Time is the time it takes the EV driver to reach the EV charging location based on the mobile application's GPS data.
- x (eq. 7) is the discount needed for the time inconvenience. This discount is based on the current strategy being adjusted and the maximum strategy price, p_max.

$$x = \frac{p_{\max} \quad - p_b}{\left[\frac{p_{max} + p_b}{2}\right]} \qquad eq. 7$$

$$\psi_k(p_c) = \frac{rating}{R_{avg}} \qquad eq. 8$$

Where:

- rating is the star rating of the EVSE location assessed.
- R_{avg} is the average star rating of the surrounding EV charging locations.

Weighted Average Payoff Function

The average of the payoffs across all strategies weighted by associated escort functions ($\bar{f}\varphi(p_b)$ and $\bar{g}\,\psi(p_c)$) was calculated using equation 9 and 10 below.

$$\bar{f}\varphi(p_b) = \frac{\sum_{k=1}^{n} w_k}{\sum_{k=1}^{n} x_k\, \phi_k} \qquad eq. 9$$

$$\bar{g}\psi(p_c) = \frac{\sum_{k=1}^{n} v_k}{\sum_{k=1}^{n} y_k\, \psi_k} \qquad eq. 10$$

$$w_k = x_k \times \phi_k \times f_k \qquad eq. 11$$

$$v_k = y_k \times \psi_k \times f_k \qquad eq. 12$$

Dynamics

The initial proportions are set for state vectors x and y for the first iteration. The payoff function, escort function, and weighted average escort function are calculated for each strategy. Afterwards, the rate of change of the population for each strategy is calculated. The new state vectors are created by adding the rate of change to the corresponding strategy proportion (eq. 13 and eq. 14).

$$x_1 = x_0 + \Delta t \times \dot{x} \qquad eq. 13$$

$$y_1 = y_0 + \Delta t \times \dot{y} \qquad eq. 14$$

3.3 Location Determination

Location Determination

We have chosen a Markov chain-based model in order to predict a user's home energy consumption in the future. In order to do this, we gathered data that described the user's energy activity during specific times of the day. This energy (in kWh) is then converted into states, where the definition of each state can be found in Table 2.

TABLE 2: STATE DEFINITIONS

State	Description
0	Absent
1	Inactive
2	Active
3	Hyperactive

This information is used to construct a transition matrix for this user, which is the tool utilized to predict their future activity (next state) based on only their current activity (current state). These probabilities are used to create an educated suggestion to a homeowner of when they should make their home available to others for charging EVs. The mathematical process and definitions for each step of this algorithm is carried out below:

Transition Matrix

$$P_{i,j} = \frac{N_{i,j}}{\sum_{k=0}^{3} N_{i,k}} \qquad eq. 15$$

$P_{i,j}$ is the probability of transitioning from state i to j. Where, $0 \le P_{i,j} \le 1$.

$N_{i,j}$ is the number of transitions from state i to state j

$N_{i,k}$ is the number of transitions from state i to state k, where k iterates from 0 to 3 (actual states).

We use eq. 15 to populate our transition matrix shown below which represents all the probabilities of a user changing from a certain state directly into a different state independently. For instance, the probability of a user in state 0 transitioning directly into a state 3 is represented by $P_{0,3}$

$$T_M = \begin{bmatrix} P_{0,0} & P_{0,1} & P_{0,2} & P_{0,3} \\ P_{1,0} & P_{1,1} & P_{1,2} & P_{1,3} \\ P_{2,0} & P_{2,1} & P_{2,2} & P_{2,3} \\ P_{3,0} & P_{3,1} & P_{3,2} & P_{3,3} \end{bmatrix} \qquad eq. 16$$

<u>Probability Matrix</u>

The probability matrix is composed of

$$s^u(t) = [P_0(t) \quad P_1(t) \quad P_2(t) \quad P_3(t)] \qquad eq. 17$$

Where, u represents a specific user and t is a certain time during the day. We obtained this from the survey. For instance, at time 0 it will look like the equation below,

$$s^u(0) = [P_0(0) \quad P_1(0) \quad P_2(0) \quad P_3(0)] \qquad eq. 18$$

If for example, a user has an initial state,

$$s^u(0) = [0 \quad 0 \quad 1 \quad 0] \qquad eq. 19$$

this user has 100% probability of being in state 2 (active). Moreover, any other subsequent $s^u(t)$ is calculated using the formula below,

$$s^u(t) = s^u(t-1) \times T_M \qquad eq. 20$$

By utilizing the above formula, we populate a 24 by 4 probability matrix that represents a whole day. The user will be required to enter a time range in which they want to serve as a charging point. Thus, decreasing the iterations of our algorithm and serving them a customized result. Per say, a user wants to participate from 9 am to 6 pm, then the 24 by 4 probability matrix will be reduce as shown below.

$$\begin{bmatrix} P_0(0) & \cdots & P_3(0) \\ \vdots & \ddots & \vdots \\ P_0(23) & \cdots & P_3(23) \end{bmatrix} \rightarrow \begin{bmatrix} P_0(9) & \cdots & P_3(9) \\ \vdots & \ddots & \vdots \\ P_0(17) & \cdots & P_3(17) \end{bmatrix} \qquad eq. 21$$

Once we find a matrix within our time constraints, we calculate the probability of all users within the same household being all-absent, all-inactive, at least one user being active and one user being hyper-active.

$$P_{all-absent} = \prod_{u \in U} P_0^u(t) \qquad eq. 22$$

$$P_{all-inactive} = \prod_{u \in U} P_1^u(t) \qquad eq. 23$$

$$P_{1+active} = 1 - \prod_{u \in U} 1 - P_2^u(t) \qquad eq. 24$$

$$P_{1+hyperactive} = 1 - \prod_{u \in U} 1 - P_3^u(t) \qquad eq.25$$

Where, U is the set of all users within a household and u is a certain user within that set.

The joint probabilities described above can be expanded in the following manner:

$$P_{all-absent} = P_0^1(t) \times P_0^2(t) \ldots \times P_0^n(t) \qquad eq.26$$

$$P_{all-inactive} = P_1^1(t) \times P_2^2(t) \ldots \times P_3^n(t) \qquad eq.27$$

$$P_{1+active} = 1 - \left[\left(1 - P_2^1(t)\right) \times (1 - P_2^2(t)\right) \ldots \times (1 - P_2^n(t))] \qquad eq.28$$

$$P_{1+active} = 1 - \left[\left(1 - P_3^1(t)\right) \times (1 - P_3^2(t)\right) \ldots \times (1 - P_3^n(t))] \qquad eq.29$$

Where n represents the total number of users in the household.

At the end of this process, the resulting matrix will contain:

$$\begin{bmatrix} P_{all-absent(time_{start})} & P_{all-inactive(time_{start})} & P_{1+active(time_{start})} & P_{1+hyperactive(time_{start})} \\ \vdots & \vdots & \vdots & \vdots \\ P_{all-absent(time_{end})} & P_{all-inactive(time_{end})} & P_{1+active(time_{end})} & P_{1+hyperactive(time_{end})} \end{bmatrix} eq.30$$

This consumption probability matrix represents the whole household. For every time period in this matrix the sum of the first two columns is calculated,

$$P_{all-absent} + P_{all-inactive} \qquad eq.31$$

This is the value used to determine which time is best suited for charging, given the selected time period by the user. The best time to charge is represented by the maximum value provided by the equation described above.

Algorithm Implementation

In Appendix B we provide the flow chart for the Markov chain-based model that was described above. The algorithm was written in C++ but can be implemented in any language of choice. Additionally, we have included two options for the homeowner; a less personalized approach defined as 'default' and a more customized approach by making use of their smart meter to gather live data. Furthermore, the homeowner is asked to select the day that represents their typical consumption activity if they select the smart meter option. The 'default' route branches off into the calculation of cut-off values for states based on the empirical data obtained in our surveys.

3.4 Data Set Determination

Our study presents an analysis of data from a survey meant to analyze user behavior to construct two distinct algorithms, from which 26 people participated that own a fossil fuel or hybrid vehicles or electric vehicles. Participants were residents of New York City and the Westchester area, as well as Con Edison Inc. customers. The survey was intended to learn how people make decisions based on ratings and how they use their appliances at home. In addition to this, we gathered market prices for different charging stations, EVs state of charge information, and electricity rate from Con Edison customers.

Survey Data

Our survey included 26 participants, 22 of whom drove fossil fuel or hybrid vehicles and 4 of whom drove electric vehicles. The survey was done in two different sections, and each of them had distinct questions for our algorithms.

Pricing algorithm

For our pricing algorithm, variable V questions in survey included: what their vehicle's battery capacity or fuel tank size is, the cost of charging or refueling, and the locations where they charge the EVs or the type of gasoline they use. For the distance and ratings needed into the algorithm, participants were questioned on how far they would go for different discounts, and how much would they pay for different average stars ratings in gas/charging stations.

The pricing algorithm required additional data, such as at what SoC EVs are at when they approach a charging station, market price of charging stations, and Con Edison electricity rates. For our Con Edison data, we gathered electricity bills from 14 different people in districts zip codes and averaged them out for our algorithm. We focused on zip codes that were geographically close to each other to concentrate our study within a more compact area. We specifically chose zip codes 10463, 10461, 10471, 10468, 10467, 10470, 10469, and 10470 as our primary targets to gather data on the market prices of different charging stations. Additionally, zip code 10701 in Yonkers was also included because of its proximity to 10471 and 10463. Two EV charging apps were utilized to gather the market prices: PlugShare and ChargePoint.

Location algorithm

For our location algorithm, the survey delved into participants usage patterns of home appliances and categorized their activities into four distinct scenarios: absent (state 0), inactive (state 1), active (state 2), and hyperactive (state 3). Participants were required to indicate the time periods they associated with each scenario over a 24-hour period to reflect their typical daily consumption. The questions asked participants included: what appliances they own, at what times they feel they are the most absent, inactive, active, or hyperactive, and at what time they are willing to open their home charger to other EV users. This last question being a more scenario question due to our limitation of actual EVs users in our survey.

Furthermore, we then collected data on when participants transitioned between these states and calculated their energy consumption in kilowatt-hours (kWh) for each state. They were also asked to specify the appliances they used in each state. We averaged the kWh usage for three different commercial brands for these appliances to establish default settings for our app, allowing users to opt for these instead of personalized settings. Moreover, we averaged out the state data from each participant to determine our app's default settings for each state.

In addition, a smart meter was installed in a participant's home to monitor their energy consumption over a week. This data was organized from lowest to highest consumption and then divided into quartiles, with state 0 representing 0% to 25%, state 1 from 25% to 75%, state 2 from 75% to 90%, and state 3 from 90% to 100%. Utilizing a smart meter connection provides a more personalized and accurate definition of states for the user. The survey also inquired about participants' willingness to allow other EV users to access their home chargers, a hypothetical scenario for most respondents.

Fig. 1. Map of zip codes in The Bronx

4 Case Study

4.1 Overview

The following section contains a case study along with a walkthrough of the application from an EV owner's perspective and a homeowner's perspective. If the user's intent is to allow their charger to be used by others, the set-up of the application will be different than for a driver looking for a charger. It is important to emphasize that the account types are not mutually exclusive, as a home charger owner could also utilize the app to find a charger for their EV, and vice versa.

Case Study

In this case study, we examine the case of Leslie Perez who is looking for a home charger while driving around the vicinity of29 Bayley Ave, Yonkers, NY. Leslie drives a Tesla Model Y vehicle. She is looking to charge for 1 hour while she finishes her run at Van Cortland Park. When she opens the ChargeBNB app, she sees multiple options available for charging. On the app she sees a map with an average rating of 4.70-stars for the nearby chargers. The time is 7 AM. She makes her selection based on a $1.36 price found for a charger on 4505 Delafield Ave, The Bronx, NY.

On the other hand, James Winston has listed his charger at 4505 Delafield Ave, The Bronx, NY on ChargeBNB, a 10-minute drive from the EV owner. James has selected a personalized default set up in the app, and entered the appliances which he uses with the corresponding times. James has also entered the times at which his charger is available, 7AM-3PM. He currently has a rating of 4.82 stars.

The rest of section 4 contains a walkthrough depiction and description of the ChargeBNB features and interface for the homeowner and for the EV owner when they open it up for the first time, and in the case of this event.

4.2 Profile Creation

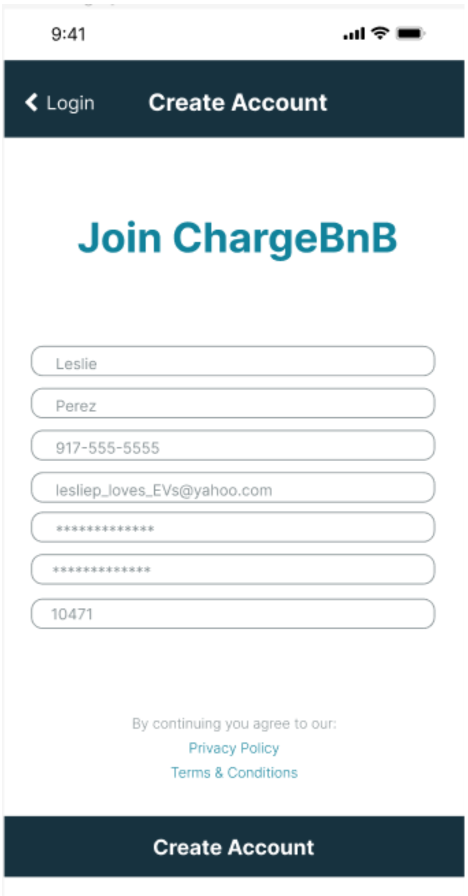

Fig. 2. EV owner Initial profile creation

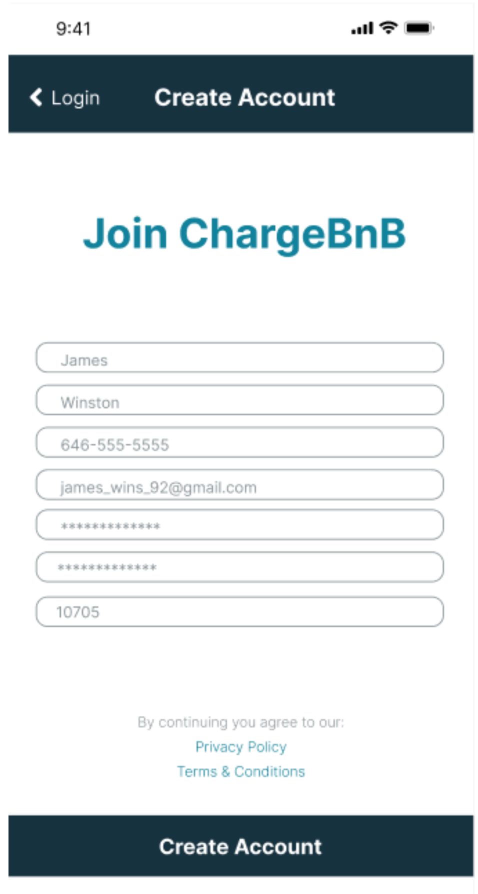

Fig. 3. EVSE owner Initial profile creation

Users deciding to use our mobile application are EV and/ or EVSE owners. When first creating their profile, they will not need to make a distinction regarding how they will use the application. This is to allow quick and easy account creation without losing customers due to inconvenience. In Figures 2 and 3, both the EV owner (Leslie Perez) and the EVSE owner (James Winston) both complete their profile with the same user demographic information.

Once a user decides to list their EVSE on the application, the profile setup deviates. The EVSE owner walkthrough is discussed next.

EVSE Owner Walkthrough

A user who decides to list their EVSE on the application will click on the button as indicated in Figure 4, and proceede to the EVSE owner setup by selecting their location on the map in Figure 5.

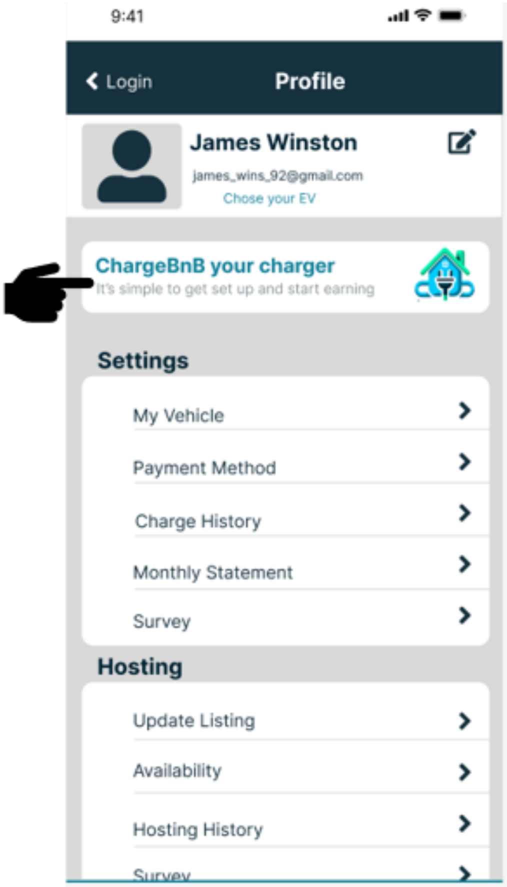

Fig. 4. James decides to list his EVSE

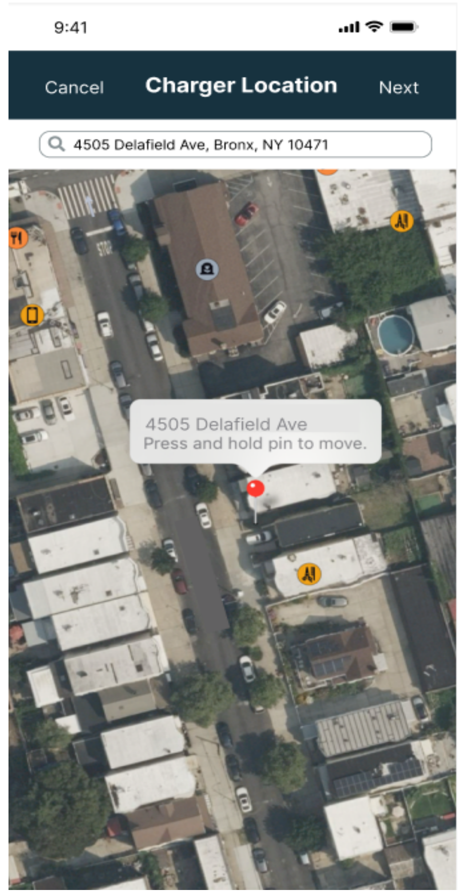

Fig. 5. Address selection on the map

Once the address is selected on the map, the EVSE owner can proceed to setting up the details for their EVSE location. The setup menu can be seen in Figure 6.

The EVSE plug and network type are setup by clicking Charger on the EVSE setup menu. The values for each can be selected and updated as needed. This step can be seen in Figure 7.

The EVSE location description is input by selecting Description on the EVSE setup menu. The description of the EVSE lets potienl EV owners coming to charge know how to access the EVSE, and if there are any additional information regarding usage. This step can be seen in Figure 8.

Finally the amenities available at and near the EVSE location can be selected on by click on Amenities on the EVSE setup menu. Additional escort functions can be created to better adjust pricing based on EV owners' preference for various amenities. This step can be seen in Figure 9.

The Survey and Availability setup are described in the Survey Walkthrough in Section 4.3.

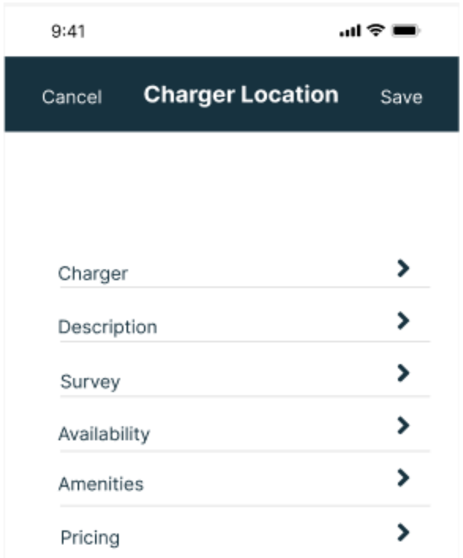

Fig. 6. EVSE Setup Menu

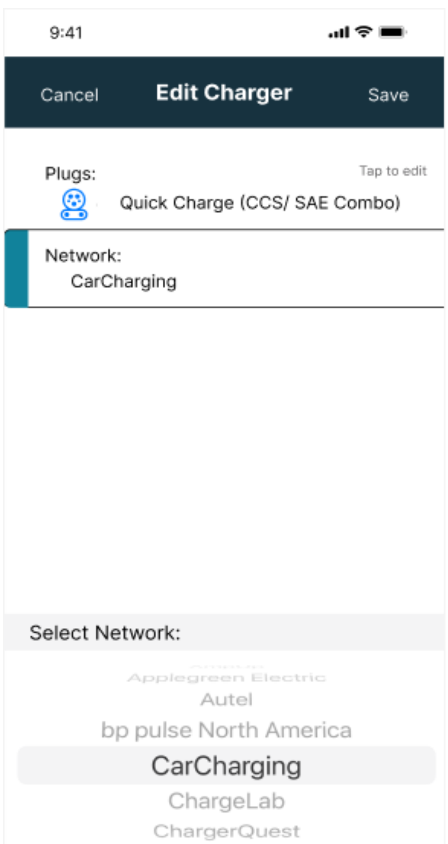

Fig. 7. EVSE Charger setup screen

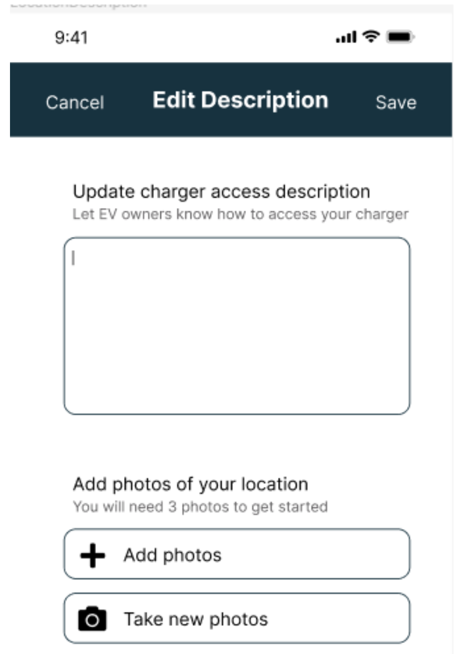

Fig. 8. EVSE Description setup screen

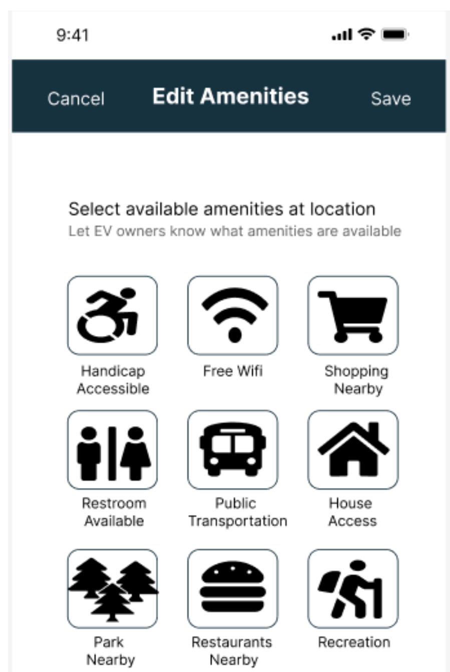

Fig. 9. EVSE Amenities setup screen

EV Owner Walkthrough

A user who decides to use ChargeBnB for EV charging needs to set up their EV on their profile. They can do this by clicking ‘Chose your EV’ as seen in Figure 10.

This takes the user to Add Vehicle screen where they can click 'Add Vehicle' to begin selecting the make and model of their EV. This is seen in Figure 11.

The EV manufacturer is first selected as seen in Figure 12. This then takes the user to a menu of models provided by the manufacturer, where they can select the model of their EV as seen in Figure 13.

Once selected their EV manufacturer and model are shown. The user can go back to make changes or select 'Add Vehicle' to update their profile with the new EV information. This is seen in Figures 14 and 15.

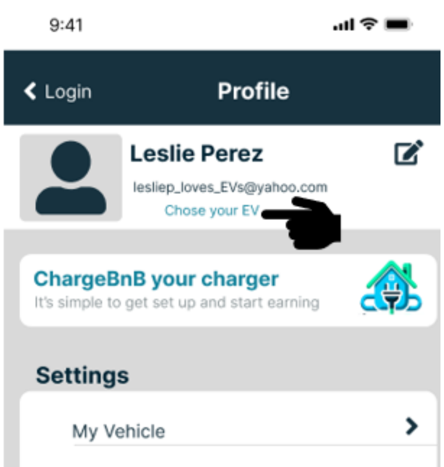

Fig. 10 EV owner selects EV model

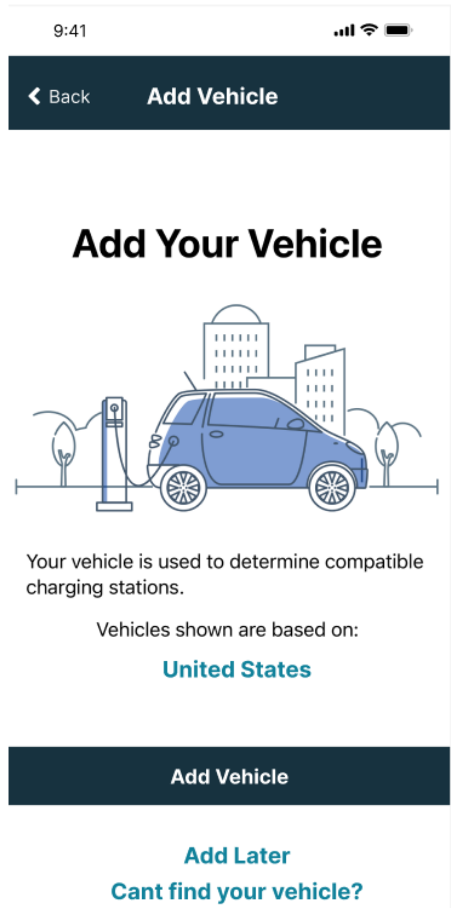

Fig. 11. Add vehicle screen

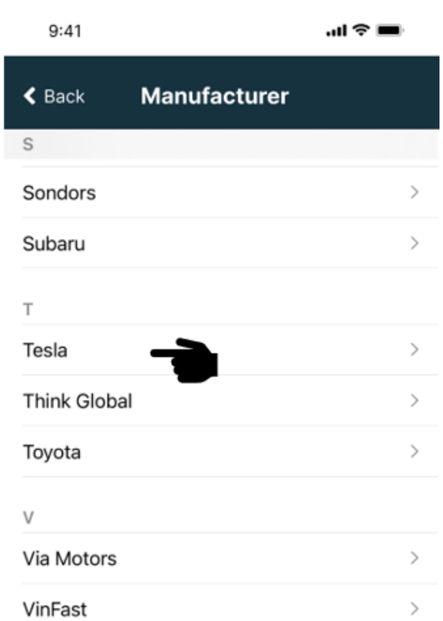

Fig. 12 Select the EV Manufacturer

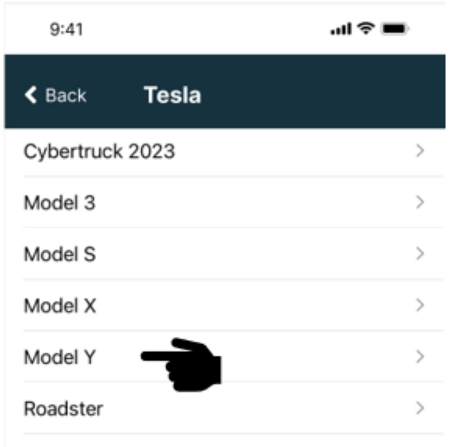

Fig. 13 Select the EV Model

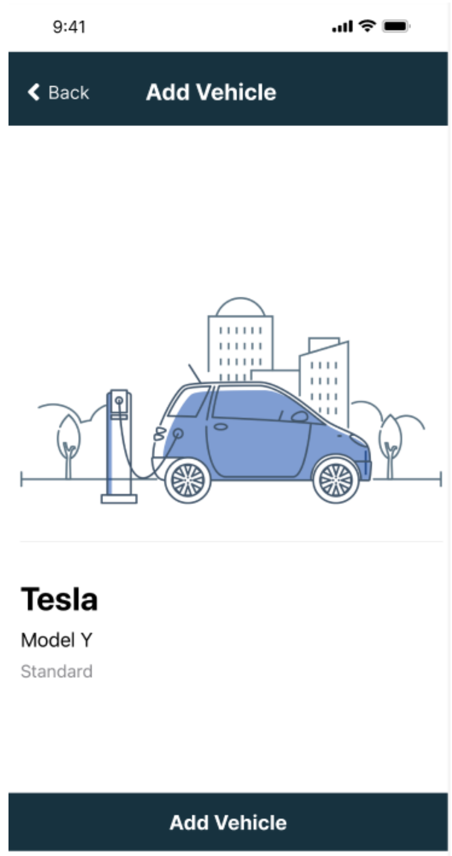

Fig. 14. Add the vehicle to profile

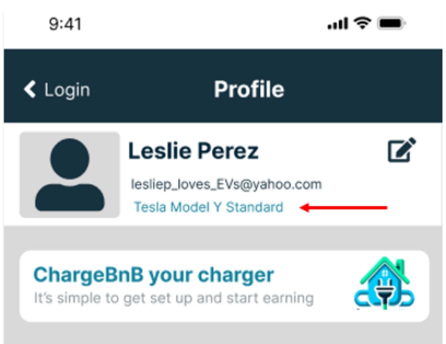

Fig. 15. Profile update with vehicle

4.3 User Surveys

EV Owner Walkthrough

A user that wishes to enroll in our mobile application must need to let us know if they are an EV owner or a homeowner with a charging station. For a detailed walk-through, 'EV user' will be showcase first. The user will be asked a series of questions to determine pricing information. If the user already has an account, they will select "Yes, I already have an account" and then proceed to select "Homeowner" as illustrated in Fig. 16.

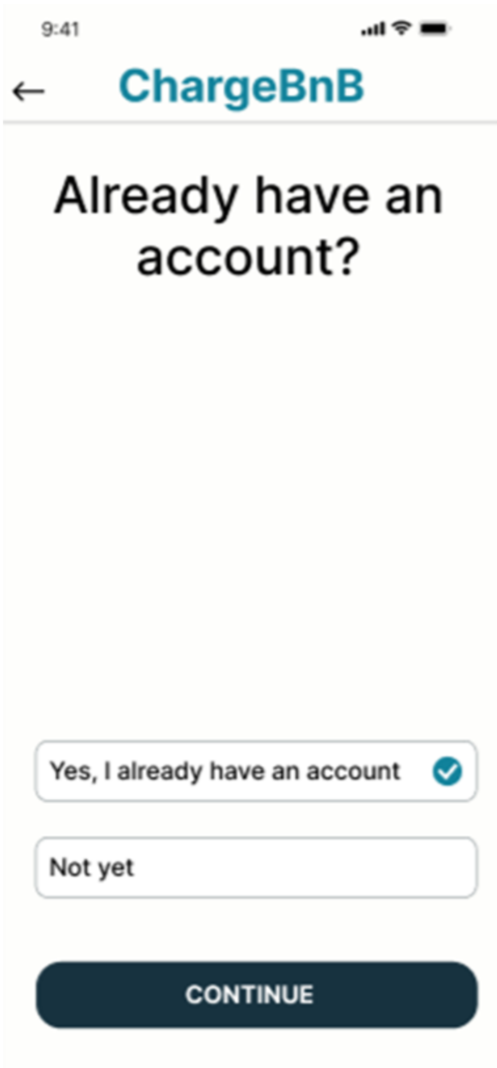

Fig. 15. User selects account information

Fig. 16. User selection enrollment

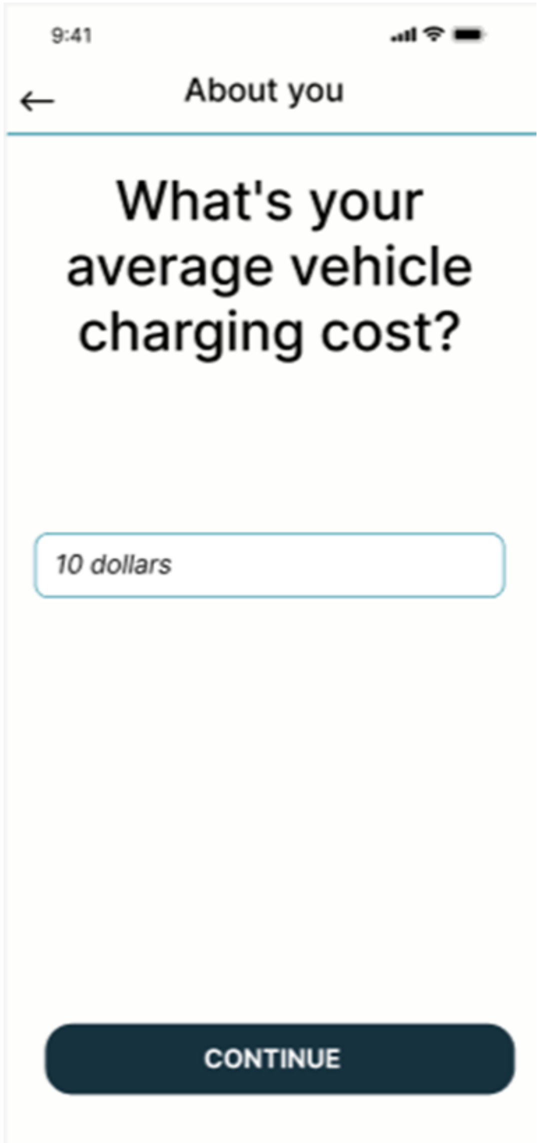

Fig. 17. EV user charging cost

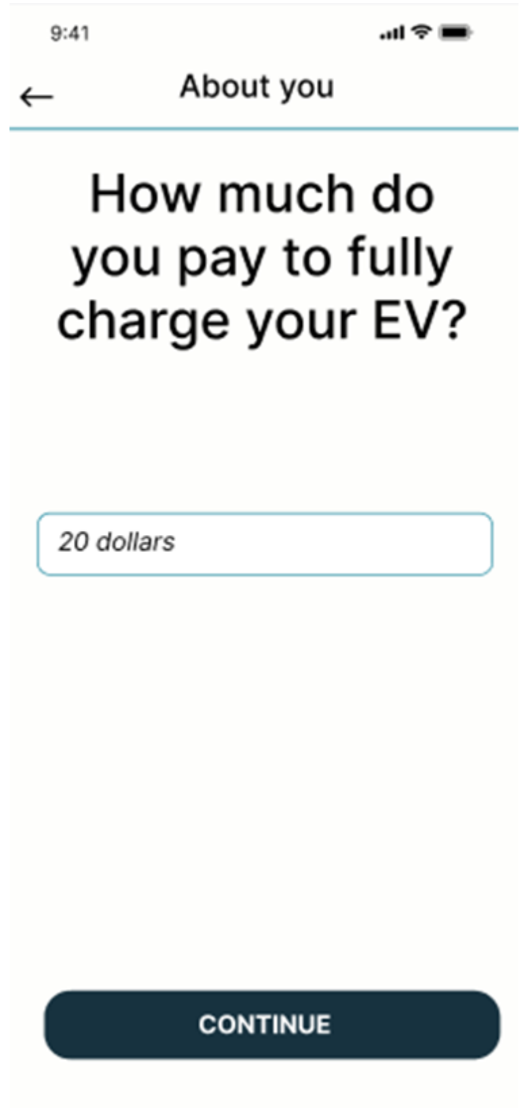

Fig. 18. EV user fully charged vehicle cost

The following questions asked to the EV owner are a series of questions to understand their battery capacity and how much they usually pay for their vehicle.

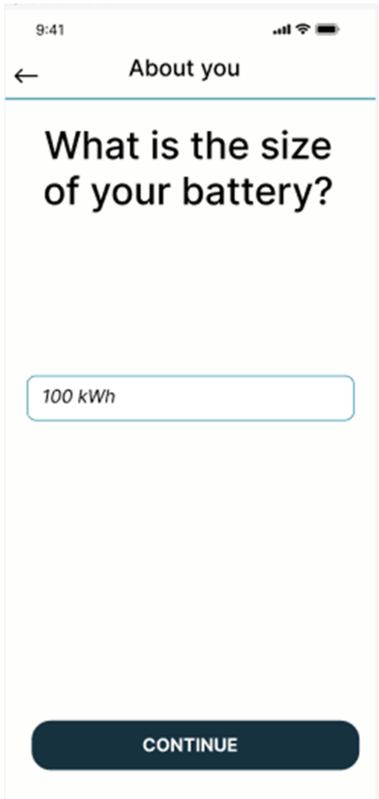

Fig 19. EV user's battery size

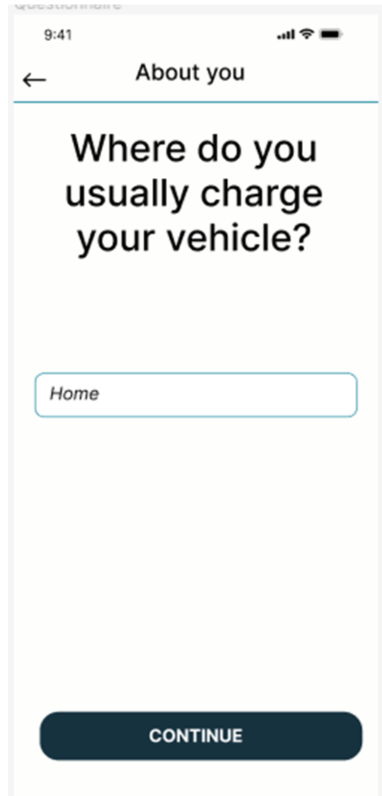

Fig. 20. EV user charging location

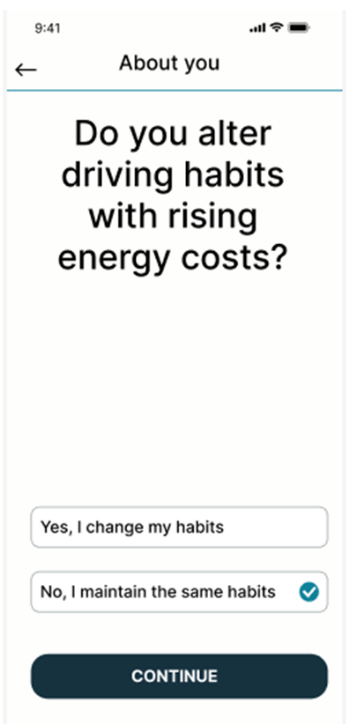

Fig. 21. EV user habits

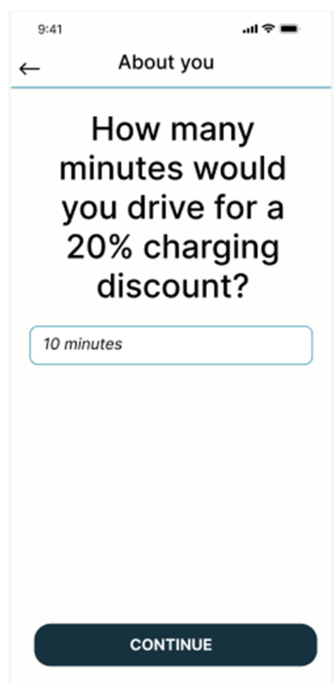

Fig. 22. EV user willingness for 20% discount

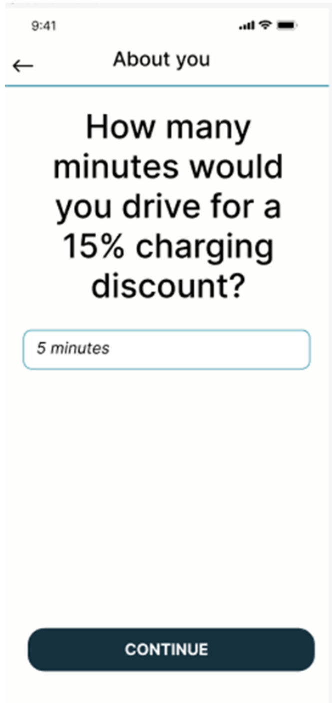

Fig. 23. EV user willingness for 15% discount

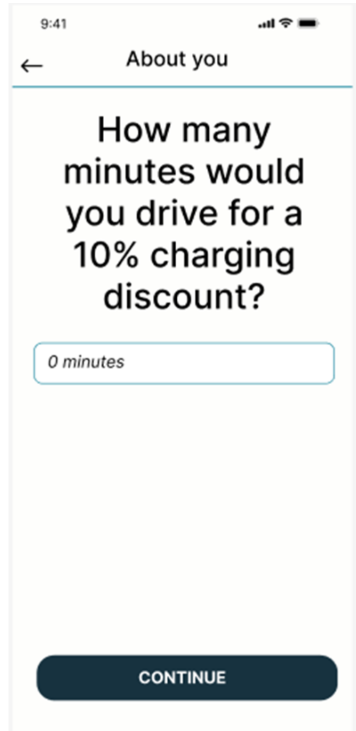

Fig. 24. EV user willingness for 10% discount

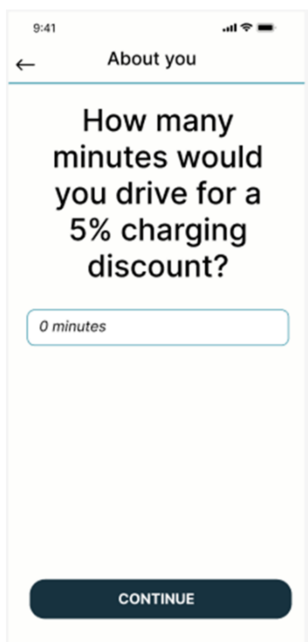

Fig. 25. EV user willingness for 5% discount

Homeowner Walkthrough

A user that wishes to sign up as a homeowner to provide a home charger will have the following questions for our location algorithm.

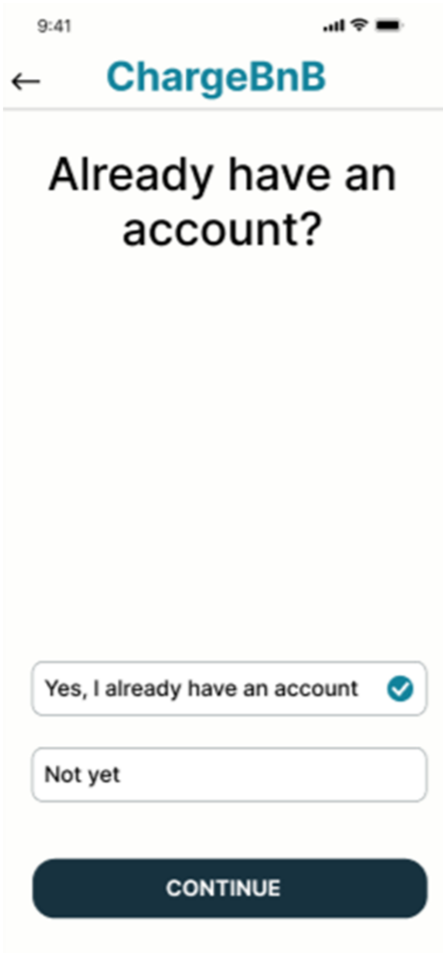

Fig. 26. User selects account information

Fig. 27. User selection enrollment

Once the user selects, they are a homeowner, they will select they would like to personalize their settings. They will proceed to select appliances from an image we set up in the mobile application. In addition to that, they will be able to input any other appliances as seen in Fig. 30.

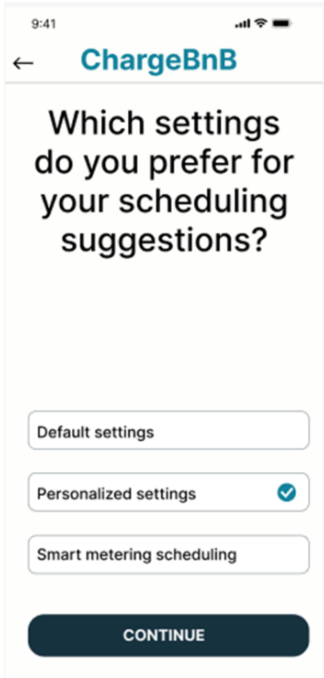

Fig. 28. User selection for settings

Fig. 29. User appliances selection

Fig. 30. Users enter extra appliances

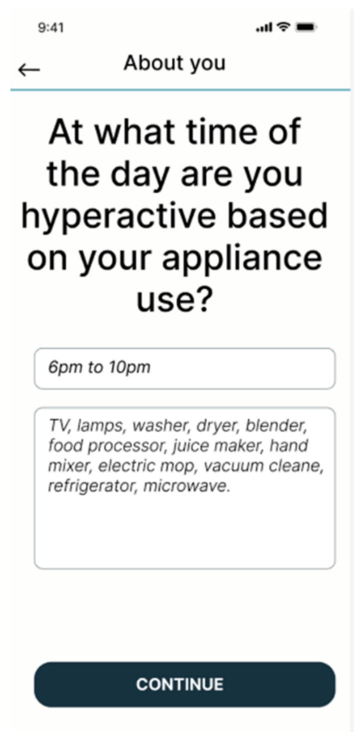

Fig. 31. User hyperactive use

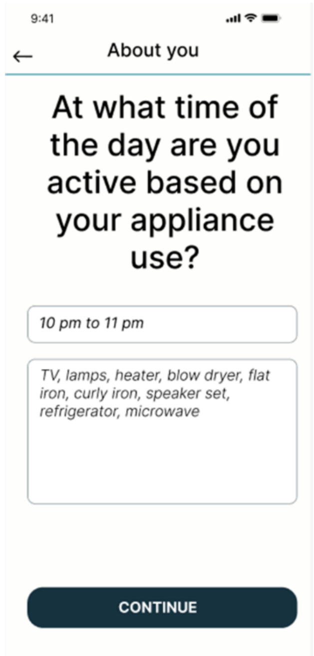

Fig. 32. User active use

Fig. 33. User inactive use

Fig. 34. User absent use

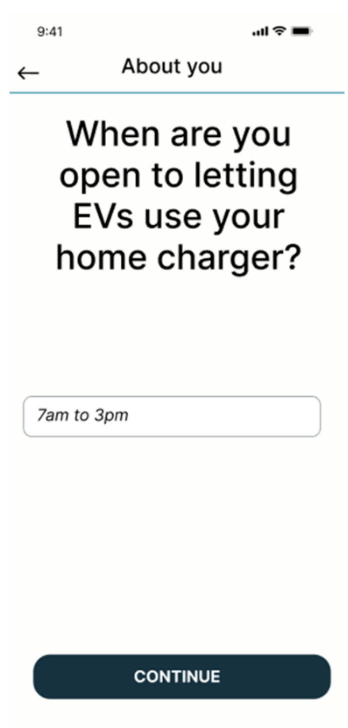

Fig. 35. User charger openings

Users will have the opportunity to enter the times where they considered to be in different states as seen in Fig.32-34. Then, Fig. 35 shows when they enter the time, they are willing to open their home changer to the public.

4.4 EV Owner User Flow

From a user whose purpose is to charge their vehicle through ChargeBnB they will navigate to a few screens making their selections as to location preferences and then choosing the most convenient charging point withing the map containing different locations, prices and availability status.

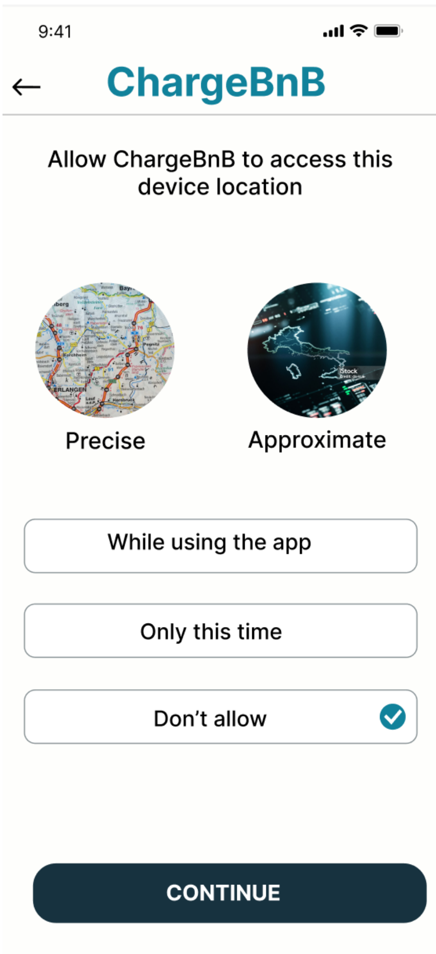

Fig. 36. asking user for privacy settings.

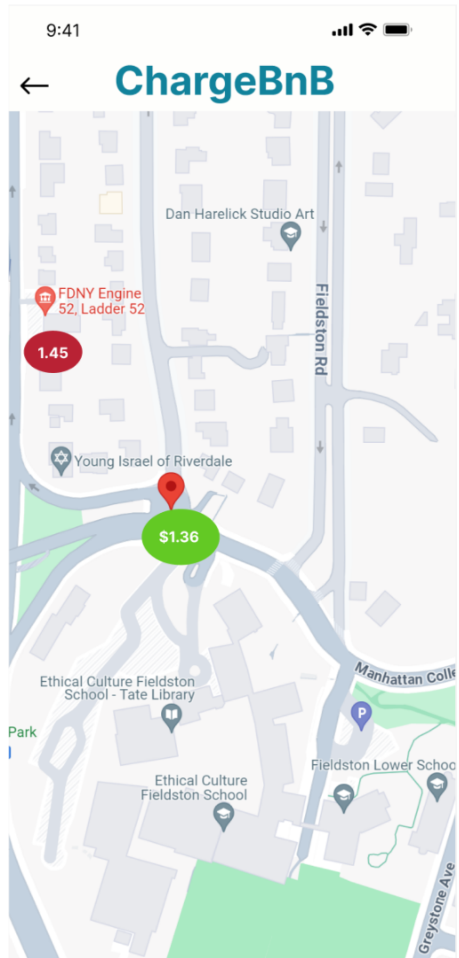

Fig. 37. displaying charges in the area.

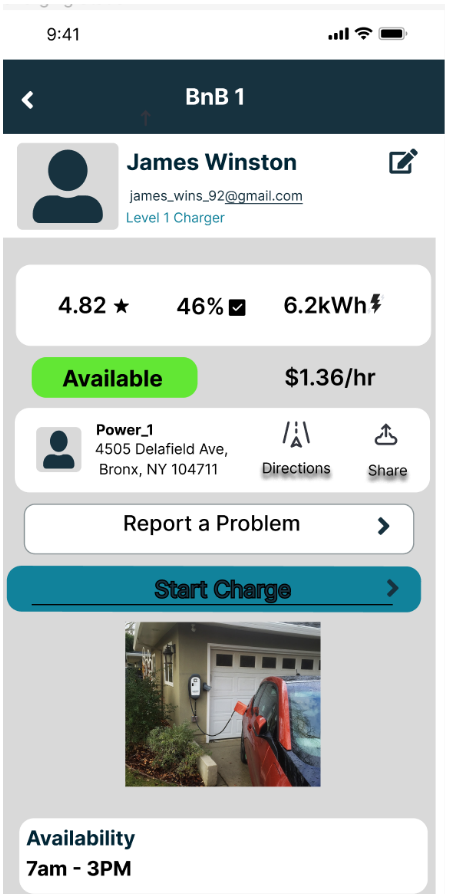

Fig. 38. Point of charge chosen by Leslie

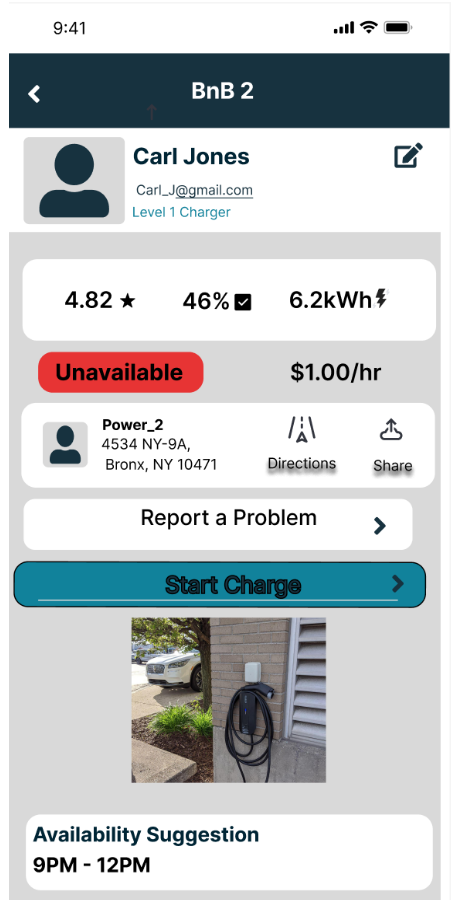

Fig. 39. Unavailable location on the map

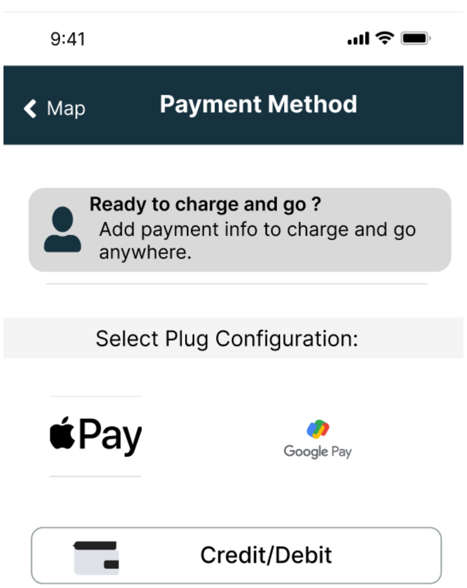

Fig.40. Payment method chose by EV-owner

As we see in fig. 39 there is a chance that a charging point is not available based on the Probability matrix recommendation to the homeowner, since their personal power usage may be relatively high at that time, thus unable to serve as a charging point.

4.5 EV Charger Owner User Flow

The EV charger owner's flow consists of the notifications received from the app, and the corresponding screens on ChargeBNB. The notifications include alerts for when somebody wants to use their charger, when someone wants to send them an inbox message, along with updates on the charging status of any vehicle owner using their charger.

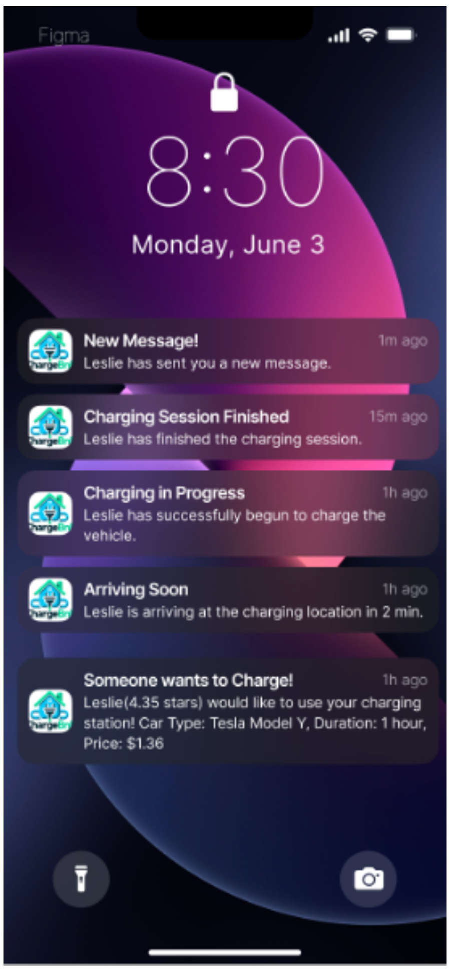

Fig. 41. Notifications for EV Charger Owner

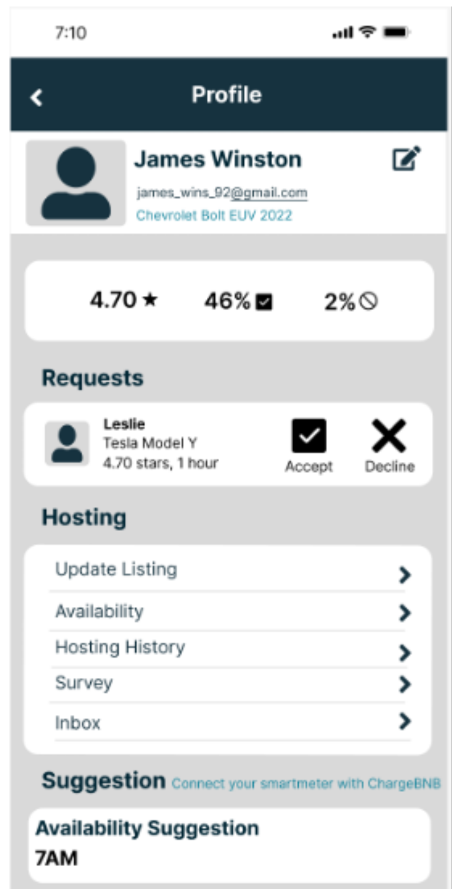

Fig. 42. EV Charger Owner Profile Screen

When James selects the 'Someone wants to Charge' notification, he will transition to his profile in the app (Fig. 42). Under the request section, he can accept or decline any pending requests to use his charger.

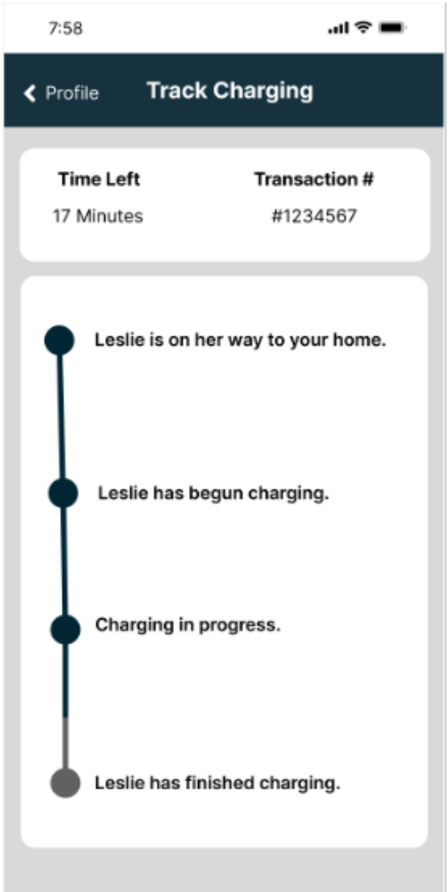

Fig. 43. EVSE Owner’s Charging Status Update

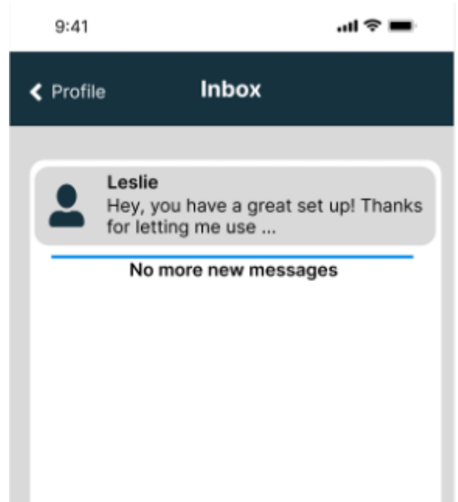

Fig. 44. EV Charger Owner’s Inbox

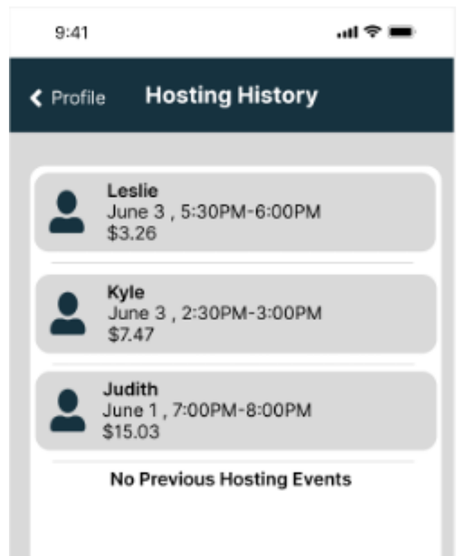

Fig. 45. EV Charger Owner’s Hosting History

Any of the charging update notifications will bring James to a screen that provides the live status of the charging session (Fig. 43). James is provided with a transaction number as well as the time left on the charging session. The new message notification will bring James to his inbox where he can view any messages from ChargeBnB, as well as from other users (Fig. 44).

James also can view his hosting history and is presented with the name and date of the charging session and the duration and total price that the session cost.

5 Results and Discussion

5.1 Location Analysis

From the case study presented, this section will analyze the results that preceded the determination of the availability of James' household.

```
double STATE_0_CUTOFF = 0.1;
double STATE_1_CUTOFF = 1.63;
double STATE_2_CUTOFF = 2.45;
```

Figure 46: James State Cut-Off Values

In Fig. 46, we can see the state cut-off values that we determined from the averages of our survey responses. Since James chose to set up his account using default values, these are the cut-offs that will be applied for his inputs in the questionnaire to determine his next state. These values could either be representative of his actual data consumption or not. This is the risk assumed by users when choose to use the default settings that we have pre-determined.

```
------ State Matrix ------
[ 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 3 3 3 3 3 1 ]
```

Figure 47: James' State Matrix

In Fig. 47, we can visualize James' state matrix, determined by the cut-offs and his input of appliance usage for different hours of the day. Every index in this matrix represents an hour of his typical day. We observe that James' is consistently in an inactive state for most of the day, until 6 PM when he jumps to a hyperactive state.

```
------ Transition Matrices ------
--- User 1 ---
[ 0.000 0.000 0.000 0.000 ]
[ 0.000 0.944 0.000 0.056 ]
[ 0.000 0.000 0.000 0.000 ]
[ 0.000 0.200 0.000 0.800 ]
```

Figure 48: James' Household Transition Matrix

The transition matrix derived for James' case, found in figure 48, is simple to understand, as his rows for state 0 (row 1) and for state 2 (row 3), contain zeros across. This occurs because from his state matrix, 0 and 2 states do not make an appearance. This simplifies the calculation of the transition for these states.

The first row of the probability matrix found in Fig. 49 contains the initial state of James' household, which is 1 (from the state matrix). This means that there is 100% probability of James being at state 1. The subsequent rows of this matrix, which pertain to each hour of the day, are calculated as described in the methodology section of the location algorithm. Noticeably, as expected, the probabilities of being at state 0 and 2 in this case, are 0 all around.

```
------ Probability Matrices ------
--- User 1 ---
[ 0.000 1.000 0.000 0.000 ]
[ 0.000 0.944 0.000 0.056 ]
[ 0.000 0.903 0.000 0.097 ]
[ 0.000 0.872 0.000 0.128 ]
[ 0.000 0.849 0.000 0.151 ]
[ 0.000 0.832 0.000 0.168 ]
[ 0.000 0.820 0.000 0.180 ]
[ 0.000 0.810 0.000 0.190 ]
[ 0.000 0.803 0.000 0.197 ]
[ 0.000 0.798 0.000 0.202 ]
[ 0.000 0.794 0.000 0.206 ]
[ 0.000 0.791 0.000 0.209 ]
[ 0.000 0.789 0.000 0.211 ]
[ 0.000 0.787 0.000 0.213 ]
[ 0.000 0.786 0.000 0.214 ]
[ 0.000 0.785 0.000 0.215 ]
[ 0.000 0.785 0.000 0.215 ]
[ 0.000 0.784 0.000 0.216 ]
[ 0.000 0.784 0.000 0.216 ]
[ 0.000 0.783 0.000 0.217 ]
[ 0.000 0.783 0.000 0.217 ]
[ 0.000 0.783 0.000 0.217 ]
[ 0.000 0.783 0.000 0.217 ]
[ 0.000 0.783 0.000 0.217 ]
```

Figure 49: James' Household Probability Matrix

```
At what time would it be okay to allow others to charge their vehicle?
7
At what time would you like to end all charging sessions for vehicles?
15
```

Fig. 50. Algorithm request for availability time

```
------ Consumption Matrix ------
[ 0.000 0.810 0.000 0.190 ]
[ 0.000 0.803 0.000 0.197 ]
[ 0.000 0.798 0.000 0.202 ]
[ 0.000 0.794 0.000 0.206 ]
[ 0.000 0.791 0.000 0.209 ]
[ 0.000 0.789 0.000 0.211 ]
[ 0.000 0.787 0.000 0.213 ]
[ 0.000 0.786 0.000 0.214 ]
```

Figure 51: James' Consumption Matrix

Given that James' input for availability were the times 7AM-3PM, this consumption matrix in Fig. 51 is a subset of the probability matrix in Fig. 49, corresponding to James' desired hours of availability.

```
Based on the information provided, 7AM is the best hour.
```

Figure 52: Location algorithm final determination/output

The final determination of a time suggestion for James is found on figure 52 to be 7AM. Looking at the consumption matrix to understand how this determination is reached. We can observe that 7AM, being the first row of the matrix, has the highest probability of James being either in state 0 or state 1.

5.2 Price Analysis

Using the case study in Section 4, the following results were determined for the EV charging using the EEGD pricing algorithm discussed in section 3.3.

Inputs obtained from the ChargeBnB application

The inputs for the pricing are obtained from the user details provided in the application. When the user opens the map to locate a charger the GPS determines the users distance from each charger, and estimates the time to arrive. The rating for the location being assessed is also provided from the application. A rating and price average is calculated based on the charging stations in the area. Based on the EV make and model and estimated SoC, an energy value is calculated.

- time = 10 minutes | The time needed to reach the assessed EVSE location
- rating = 4.82 | The rating of the EVSE location being assessed
- R_avg = 4.7 | The average rating of nearby EVSE locations
- E = 30.8 | The energy needed to charge the Tesla Model Y
- $\hat{p}$ = 1.315 | The average market price of nearby public charging stations

Data calculated based on inputs

From the inputs provided the following data is calculated to facilitate the creation of the initial state matricies and determine the escort functions used.

- p_max = $1.3605/ kWh | Using equation 3
- p_min = $0.9205/kWh | Using equation 4
- φ_k = 0.1799ln(x) + 0.6171 | From Table 1, time = 10
- ψ_k = 1.026 | Using equation 8

Prices calculated based on inputs:

The initial state vector for the supply and demand prices are created with the strategies ranging from p_min to p_max, and the population proportion (0.0222) equally split between all strategies as seen in Figure 52.

```
state_vector:  [(0.9205, 0.02222222) (0.9305, 0.02222222) (0.9405, 0.02222222)
 (0.9505, 0.02222222) (0.9605, 0.02222222) (0.9705, 0.02222222)
 (0.9805, 0.02222222) (0.9905, 0.02222222) (1.0005, 0.02222222)
 (1.0105, 0.02222222) (1.0205, 0.02222222) (1.0305, 0.02222222)
 (1.0405, 0.02222222) (1.0505, 0.02222222) (1.0605, 0.02222222)
 (1.0705, 0.02222222) (1.0805, 0.02222222) (1.0905, 0.02222222)
 (1.1005, 0.02222222) (1.1105, 0.02222222) (1.1205, 0.02222222)
 (1.1305, 0.02222222) (1.1405, 0.02222222) (1.1505, 0.02222222)
 (1.1605, 0.02222222) (1.1705, 0.02222222) (1.1805, 0.02222222)
 (1.1905, 0.02222222) (1.2005, 0.02222222) (1.2105, 0.02222222)
 (1.2205, 0.02222222) (1.2305, 0.02222222) (1.2405, 0.02222222)
 (1.2505, 0.02222222) (1.2605, 0.02222222) (1.2705, 0.02222222)
 (1.2805, 0.02222222) (1.2905, 0.02222222) (1.3005, 0.02222222)
 (1.3105, 0.02222222) (1.3205, 0.02222222) (1.3305, 0.02222222)
 (1.3405, 0.02222222) (1.3505, 0.02222222) (1.3605, 0.02222222)]
```

Fig, 52. Initial state matrix for both EV and EVSE strategies

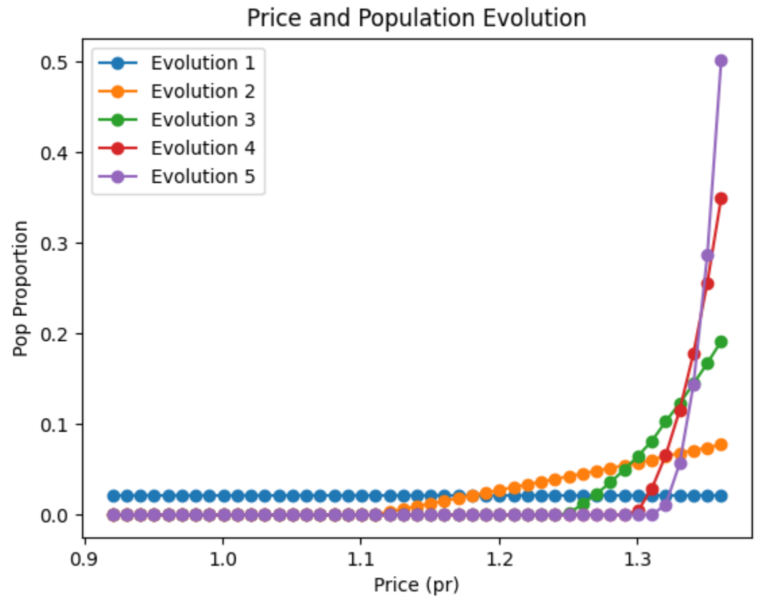

Fig. 53. Evolution of prices and population

After each evolution of the algorithm, the state vector changes. The population proportion associated with each prices is adjusted to by both the payoff function and the associated escort function. The changes in states for the EVSE owner can be seen in Figure 53.

TABLE 3: PRICES AND ASSOCIATED POPULATION PERCENTAGES

Price	EVSE % Pop	EV % Pop
0.9205	0.00%	29.11%
0.9305	0.00%	20.85%
0.9405	0.00%	14.56%
0.9505	0.00%	9.86%
0.9605	0.00%	6.44%
0.9705	0.00%	6.18%
0.9805	0.00%	4.52%
0.9905	0.00%	3.44%
1.0005	0.00%	2.77%
1.0105	0.00%	2.40%
1.0205	0.00%	2.22%
1.3005	0.00%	2.17%
1.3105	0.00%	2.16%
1.3205	**1.17%**	**2.16%**
1.3305	**5.67%**	**2.16%**
1.3405	**14.37%**	**2.16%**
1.3505	**28.66%**	**2.16%**
1.3605	**50.13%**	**2.16%**

The prices determined by the EEGD algorithm can be seen in Table 3. The initial population distribution for both EV and EVSE owners was 2.22% across all prices.

The table shows that for the EV owner the most preferred price is $0.9205/kWh at 29.11%. With the next price of $0.9305/kWh at 20.085%. For the EV owner, the distribution for the prices remains higher than the initial value up to $1.0205/kWh which has a distribution equal to the initial value. At that point, the distribution levels off at 2.16% for the remaining prices.

The distribution does not decrease to 0% for the higher prices due to the escort function accounting for the market prices, and adjusting EV owner strategy results based on the nearby market prices.

The table shows that the EVSE owner population distribution is 0% for all prices below $1.3105/ kWh, and is the maximum level of 50.13% for the maximum price of $1.3605/ kWh. The EVSE owner was not incentivized to lower his price as his charging station had a higher than average user rating.

Therefore, the price chosen to present to the EV owner on the ChargeBnB application in the case study is **$1.3605/ kWh**. As all prices where both the EV and EVSE owners have a non zero population distribution, the EV owner has the same distribution of 2.16%. If there are no prices that have a population distribution > 0% for both users, then the lowest EVSE price will be used.

5.3 Data Analysis

Our collected data concluded that 84% of our participants had fossil fuel or a hybrid vehicle while 16% owned an electric vehicle.

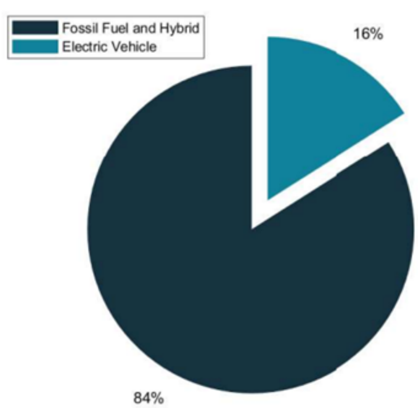

Figure 1. Participant vehicle types

Our Con Edison electricity rate for The Bronx was gathered from 14 different participants to averaged out the tariff that is usually paid by customers. Table 3 illustrates the amount paid for the billing period from October to November, the kWh they used for the billing period, the total rate and in what zip code in The Bronx they are located. Our average rate was set to be 0.4575 cents per kWh.

To calculate the total rate, we used formula #:

$$Total\,rate = \frac{Amount\ paid}{kWh} \qquad eq. 32$$

For the average rate, we performed formula #:

$$Electric\ average\ = \frac{1}{N}\sum_{x=1}^{N} Rate_x \qquad eq. 33$$

- N: total number of customers
- X: user number
- $Rate_x$: rate for user x

TABLE 3. CON EDISON ELECTRICITY RATES FOR THE BRONX

User	Amount Paid	kWh	Total Rate	Zip code
1	154.12	458	0.33650655	10451
2	96.99	261	0.371609195	10452
3	190.98	510	0.374470588	10453
4	416.31	1165	0.357347639	10454
5	49.33	83	0.594337349	10457
6	50.21	92	0.54576087	10458
7	114.69	287	0.399616725	10458
8	72.13	157	0.459426752	10460
9	41.89	63	0.664920635	10461
10	76.53	157	0.487452229	10463
11	94.61	264	0.358371212	10463
12	121.77	294	0.414183673	10465
13	181.39	498	0.364236948	10468
14	128.07	380	0.337026316	10469

Furthermore, we computed the State of Charge (SoC) for the top 10 electric vehicle models as listed by [20]. These specific models were selected for their demand in the market, being among the highest-selling EVs in 2022, and representing a diverse array of models. Table 4 depicts the list of cars. For our study we selected the SoC when the vehicle is at home.

TABLE 4. ELECTRIC VEHICLE MODELS

			% SoC		
User	Model	Battery Capacity kWh	Home	Workplace	Public Charger
1	Tesla Model Y - RWD	60	24.60	28.68	23.46
2	Tesla Model 3 - RWD	50	20.50	23.90	19.55
3	Ford Mustang Mach-E - RWD	68	27.88	32.50	26.59
4	Chevy Bolt EV/EUV	65	26.65	31.07	25.42
5	Tesla Model S - RWD	85	34.85	40.63	33.24
6	Tesla Model X - 90D	100	41.00	47.80	39.10
7	Hyundai Ioniq5 - SE Standard	58	23.78	27.72	22.68
8	VW ID.4 - RWD	58	23.78	27.72	22.68
9	Kia EV6 - RWD	58	23.78	27.72	22.68
10	Rivian R1T - AWD Standard	105	43.05	50.19	41.06
Average			28.99	33.79	27.64

Furthermore, the market prices for 37 charging stations located in proximity to Riverdale were computed and averaged out to be 1.3242. (See Appendix A for table)

6 Conclusion

In our research paper, we introduce ChargeBnB, a novel mobile application designed to facilitate EV charging by connecting EV owners with residential EVSE owners. ChargeBnB provides users with the price and location of available chargers, connecting users who need to charge their EV with owners of EV charging equipment.

In order accomplish this a dynamic pricing algorithm using escort evolutionary game dynamics is used to present a customized price to the user based on their specific data such as location, car type, and rating of the charging location. Additionally, a Markov chain-based stochastic algorithm was used to determine the optimal time for EVSE owners to allow EV charging, thus updating the location of available chargers dynamically. Empirical data informs our algorithmic assumptions.

Our case study demonstrates that EV and EVSE owners can conveniently arrange charging sessions through the app at mutually agreed prices, times, and locations. The app adapts to user needs and preferences, with ongoing data collection through user survyes, enhancing algorithm accuracy for time and price recommendations.

Future improvements include incorporating machine learning for increased accuracy, additional features, and an enhanced user experience.

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Appendix A

Table #. Market price for charging stations

<table>
<tr><th>No.</th><th>Price (kWh)</th><th>Name</th><th>Location</th><th>Note</th></tr>
<tr><td rowspan="3">1</td><td>0.25 (12 am to 8 am)</td><td rowspan="3">NYC FLEET/DPR_VCP-S2</td><td rowspan="3">10471</td><td rowspan="3">1 charger</td></tr>
<tr><td>0.30 (8 am to 10 pm)</td></tr>
<tr><td>0.25 (10 pm to 12 am)</td></tr>
<tr><td>2</td><td>0.23</td><td>SKYVIEW APARTME / SKYVIEW ST2</td><td>10471</td><td>2 Chargers / Difficult to find (reviews)</td></tr>
<tr><td>3</td><td>0.23</td><td>SKYVIEW APARTME / SKYVIEW ST1</td><td>10471</td><td>2 Chargers / Difficult to find (reviews)</td></tr>
<tr><td rowspan="3">4</td><td>0.25 (12 am to 8 am)</td><td rowspan="3">NYC FLEET / DPR_VCP-S1</td><td rowspan="3">10471</td><td rowspan="3">1 charger</td></tr>
<tr><td>0.30 (8 am to 10 pm)</td></tr>
<tr><td>0.25 (10 pm to 12 am)</td></tr>
<tr><td>5</td><td>0.5</td><td>Briar Oaks</td><td>10463</td><td>Idle fee of $10 per hour, one review says good for level 2, another one says could not find chargers</td></tr>
<tr><td rowspan="4">6</td><td>AUA-10311: 6 am to 9 pm : $2.50/hr n 9 pm to 6 am : $1/hr</td><td rowspan="4">Bronx Van Cortlandt Village</td><td rowspan="4">10468</td><td rowspan="4">4 stations</td></tr>
<tr><td>AUA-10296: 6 am to 9 pm : $2.50/hr n 9 pm to 6 am : $1/hr</td></tr>
<tr><td>AUA-10328: 6 am to 9 pm : $2.50/hr n 9 pm to 6 am : $1/hr</td></tr>
<tr><td>AUA-10322: 6 am to 9 pm : $2.50/hr n 9 pm to 6 am : $1/hr</td></tr>
<tr><td rowspan="2">7</td><td>AUA-10300: 6 am to 9 pm : $2.50/hr and 9 pm to 6 am : $1/hr</td><td rowspan="2">Dekalb Ave Parking/Charging</td><td rowspan="2">10467</td><td rowspan="2">2 stations</td></tr>
<tr><td>AUA-10283: 6 am to 9 pm : $2.50/hr and 9 pm to 6 am : $1/hr</td></tr>
</table>

8	AUA-10290: 6 am to 9 pm : \$2.50/hr and 9 pm to 6 am : \$1/hr AUA-10293: 6 am to 9 pm : \$2.50/hr and 9 pm to 6 am : \$1/hr	Putnam Pl Parking/Charging	10467	2 stations
9	\$4.00/session, time limit 8 h	New York Botanical Garden - Parking Garage	10458	1 station, 2 plugs / \$17 parking Tues-Friday, and \$20 Satur-Monday
10	AUB-19082: \$3.00 (USD) per hour for first 1 hour(s) and \$10.00 (USD) per hour after 1 hour(s) AUB-19098: \$3.00 (USD) per hour AUB-19111: \$3.00 (USD) per hour AUB-19121: \$3.00 (USD) per hour AUB-19122: \$3.00 (USD) per hour AUB-19120: \$3.00 (USD) per hour	Popeyes	10469	6 stations
11	12:00 AM-5:59 AM - \$2/kWh 6:00 AM-9:59 PM - \$1/kWh 10:00 PM-11:59 PM - \$2/kWh	Key Food Supermarket	10461	1 station
12	0.46	Northeast Bronx YMCA	10466	Proximate to 10467 - 4 stations, has some bad reviews
13	0.35/kWh + While charging: 2.00/hr (after 9:00 PM) + While charging: 2.00/hr (12:00 AM-6:00 AM) + While parked, not charging: 25.00/hr after 45 mins (7:00 AM-11:55 PM)	Yonkers Police Department	10705	Proximate to 10471
14	\$2.00 (USD) per hour	Warburton Garage	10701	11 Stations - Proximate to 10471

Appendix B

Location Algorithm Flow Chart