Viability Analysis of Electric Taxis Using New York City Dataset

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ABSTRACT
This paper examines the viability of electric taxis, namely whether it will be profitable for taxi drivers to adopt electric taxis, in comparison with conventional taxis with internal combustion engines. This paper provides a data analytic investigation using a large dataset of real-world taxi trips in New York City. We model the taxi service strategy by Markov Decision Process. Under this model, we observe that in order to enable an electric taxi driver (using Nissan Leaf) to reach a comparable profit with a conventional taxi driver, the minimum required battery capacity is 45 kWh, more than that of the existing one. We observe that the potential profit of the electric taxi driver can be 3% higher than that of a median conventional taxi driver with sufficient battery capacity, despite nowadays low gas price.

CCS CONCEPTS
•Applied computing →Transportation;

KEYWORDS
Electric Vehicles, Data Analysis

ACM Reference format:

1 INTRODUCTION
Electric vehicles (EVs) are becoming a crucial means of transportation in recent years because of affordable prices and low emissions. One of the barriers preventing wide EV adoptions is the limited driving range. With the increase of battery capacity, the driving range has been extended to more than 200 kilometers in many production EVs such as Chevrolet Bolt and Tesla. Generally, the driving ranges of production EVs are sufficient for daily commutes of personal purposes. However, much longer driving range is normally required by logistics and vehicle fleet companies. These companies are important users, as they can deploy a large number of EVs.

In particular, taxi companies are major potential users of electric vehicles. As in 2017, there are around 13,000 taxi cabs in New York City. The average driving distance is around 290 kilometers per shift (i.e., 12 hrs). There is a huge potential to reduce exhaust gas emissions by adopting electric taxis. However, it is not clear whether taxi drivers are willing to switch to electric taxis from conventional taxis with internal combustion engines. Especially, electric taxis may suffer from limited driving range and hence lower revenue. The driving range of Tesla (as in 2017) may suffice to meet the required driving distance, but are too costly to be practical taxis. Therefore, an analysis of viability of electric taxis is useful to examine the profitability of electric taxi drivers. Furthermore, such an analysis can set a benchmark for determining proper governmental subsidy for electric taxis to promote their adoptions.

In general, the profit of a taxi driver is determined by the strategy of passenger searching and efficiency of passenger delivery. A taxi driver can drop off a passenger and wait in the same location for the next passenger, or search for the passengers by roaming the streets. Skillful taxi drivers can deliver passengers efficiently by choosing a route with less traffic. The strategies of taxi drivers may be improved by a recommendation system that predicts the location of demands. Such a recommendation system can utilize a large historical taxi trip dataset for demand prediction.

In this paper, we model the taxi service strategy by Markov Decision Process (MDP). Under this model, we determine the optimal policy that maximizes the profit based on New York City taxi trip dataset. We then compare the profits between an electric taxi driver and a conventional taxi driver with internal combustion engine (ICE) vehicles. We study how to improve the profitability of the electric taxi driver.

2 RELATED WORK
Analyzing taxi trip dataset has been considered by several research papers in data mining and intelligent transportation system. One of popular topics is the profit/revenue improvement for taxi drivers by constructing a recommendation system to assist the drivers to find passengers more efficiently. The basic idea is to identify good taxi service strategies [10]. The authors observed several characteristics of taxi service strategies. Their study shows that searching passengers near the drop-off location of previous passengers results in a higher revenue. They also found that better taxi drivers can deliver the passengers efficiently by choosing an uncongested route. Other studies focus on improving the profit/revenue of the taxi drivers. One approach is to maximize the profit of the next trip for taxi drivers [9]. The authors developed a recommendation system for both taxi drivers and passengers. The study shows that experienced taxi drivers usually pick up passengers and waits at certain locations, and they are usually cognizant of particular events like train arrivals or ends of movies. Therefore, the system recommends hot spots for taxi drivers and passengers. Instead of recommending a sequence of pick-up locations, another approach maximizes the profit along a route which is connected to the sequence of locations [5]. The recommendation of top-k profitable driving routes
are computed based on a route segment network with profits and pick-up probabilities from historical taxi trip data. For optimizing the decisions for the following actions, Markov Decision Process (MDP) is used to maximize the revenue in [6]. The optimal actions are determined by maximizing the taxi drivers’ revenue from the associated MDP.

Limited driving range is one of the barriers preventing wide EV adoptions. Therefore, estimating the driving range for EVs has been a subject of a number of research papers. The driving range of EVs is highly affected by driving speed and auxiliary loading (e.g., air conditioning). A considerable amount of energy will be consumed by auxiliary machines during traffic congestions, which decreases the driving range significantly. A blackbox model is used to construct personalized energy consumption model for EVs and plug-in hybrid EVs (PHEVs) [2, 8]. Their model considers driving behavior and auxiliary loading to estimate the energy consumption of vehicles. Also, the return on investment (ROI) for taxi companies transitioning to EVs has been studied in [1].

3 NEW YORK CITY TAXI TRIP DATASET

We first describe the taxi trip dataset of New York City (NYC) in 2013. We list the attributes of dataset that are used in our study. For each data record (i.e., a trip), it is composed of following attributes:

1. Taxi ID
2. Trip distance and duration
3. Times of pick-ups and drop-offs of passengers
4. GPS locations of pick-ups and drop-offs of passengers

The numbers of taxi trips of NYC dataset on different days of 2013 are depicted in Fig.1a. There are about 400,000 trips per day and the average trip distance is around 4.5 kilometers. Fig.1b displays the pick-up locations on January 16 at 8:00-9:00 AM. The k-mean clustering was employed to cluster pick-up locations by 200 clusters. The sizes of circles indicate the number of pick-up locations. We observe most of pick-up locations in Midtown Manhattan.

(a) Numbers of trips and average trip distance (b) Pick-up events in NYC of NYC taxi trip dataset.

Figure 1: Overview of NYC taxi trip dataset.

4 MARKOV DECISION PROCESS

Following [6], we employ Markov Decision Process (MDP) approach to model the taxi service strategy. MDP comprises of a set of states (S) and a set of possible actions (A) that transfer the states from one to another. Each action transfers the current state to a new state with a probability (P) and a corresponding reward (R). The objective to find the optimal actions that maximize the profit.

4.1 System States

The state for a taxi is described by two parameters – current location and current time. The details are explained as follows:

- **Location**: We first construct a road network using OpenStreetMap (OSM) junction data and NYC taxi trip data. Each pick-up or drop-off locations is assigned to the nearest junctions in OSM. We remove the records that contain 1) incomplete data information such as missing time stamp or GPS location, 2) the trip distance larger than 50 kilometers, or 3) the trip duration longer than 1 hour. For each record, the pick-up and drop-off locations are added into network as nodes, and a directed edge pointing from the pick-up location to the drop-off location is assigned.
- **Time**: We use 1 minute as the interval of a time slot.

We denote the system state of a junction *i* at time *t* by *S* = (*i*, *t*).

4.2 Actions

The allowable actions from the current junction to the others are the successors of the current junction in the road network. We also allow the option of staying at the same location as one of the possible actions. We denote the action from junction *i* to junction *j* as *A*_i,j.

4.3 Preliminary Parameters of Profit Model

We explain the preliminary parameters used in the profit model in this section. The details of obtaining each parameter will be discussed in the next section.

The probability parameters are defined as follows:

- **P*_i,t*^p_*i,t*: The probability of successfully picking up passengers in junction *i* at time *t*.
- **P*_i,t*^d_*i,t*: The probability of the passengers move from junction *i* to junction *j* at time *t*.

The time parameters are defined as follows:

- **T_*i,j*: The required time to travel from junction *i* to junction *j* at time *t*.
- **T*^w*: When the taxi driver arrives at each junction, it will spend some time to wait for passengers. For convenience, we set the waiting time to be 1 minute.

The profit is defined as follows:

- **F_*i,j*: The profit of transporting passengers from junction *i* to junction *j*. The profit is calculated using the fare rule of New York taxi and the cost of energy sources. There are different small surcharges in different time and days, and hence, the profit is also time-dependent.

4.4 State Transition and Objective Function

One property of Markov model is the state transition, one state will transit to another state given a decision (action). We describe the state transition for a taxi when it makes an action. Assuming the current state is *S* = (*i*, *t*), an action *A*_i,j is taken and thus **T**^j_*i,j,* elapses, where junction *j* is one of the successors of junction *i*. 
The taxi will move from junction \(i\) to junction \(j\) and then search for passengers around the junction with a period of time \(T^w\). For clarity, we denote \(T_{i,j,t}^a\) as the completion time of an action, where \(T_{i,j,t}^a = T_{i,j,t}^t + T^w\). Then, there will be two possible consequences of an action:

1. The taxi successfully pick up passengers in junction \(j\) with probability \(P^p_{j,t+T_{i,j,t}^a}\). Then the passengers will go to a destination \(k\) with probability \(P^d_{j,k,t+T_{i,j,t}^a}\). Meanwhile, the taxi driver will receive a fare of amount \(F_{j,k,t}\). The taxi will start to make the next action at junction \(k\) again. Hence, the state of the taxi becomes \(S' = (k, t + T_{i,j,t}^a + T_{j,k,t+T_{i,j,t}^a}^t)\).

2. The taxi does not find a passenger after the action time \(T_{i,j,t}^a\) in junction \(j\) with probability \(1 - P^p_{j,t+T_{i,j,t}^a}\). The taxi driver will not receive any fare in this case. Then the taxi driver will start to make next action at junction \(j\). Therefore, the state of the taxi becomes \(S' = (j, t + T_{i,j,t}^a)\).

The objective of MDP model is to maximize the total expected profit in the current state. The maximal expected profit for an action \(A_{i,j}\) with state \(S = (i, t)\) is expressed as \(R^a(S, A_{i,j})\) shown in Eq. 1. The expected profit of the action is the received profit deducts energy cost of the action.

\[
R^a(S, A_{i,j}) = \delta \left( E(j, t + T_{i,j,t}^a) + E^e_{i,j,t} \right) \cdot \left( (1 - P^p_{j,t+T_{i,j,t}^a}) R(j, t + T_{i,j,t}^a) \right) \\
+ \sum_{k=1}^{J.alt} P^p_{j,t+T_{i,j,t}^a} P^d_{j,k,t+T_{i,j,t}^a} \left( F_{j,k,t} + R(k, t + T_{i,j,t}^a + T_{j,k,t+T_{i,j,t}^a}^t) \right) \\
- E^e_{i,j,t} \cdot U
\]

where

- \(R(j, t)\) is the maximal expected profit of state \((j, t)\).
- \(J\) is the number of junctions in the road network.
- \(E(j, t + T_{i,j,t}^a)\) is the expected energy consumption at state \(S = (j, t + T_{i,j,t}^a)\). Tracking energy consumption of the state is essential when employing MDP to EVs, since the action become infeasible when the EV running out of battery. If the expected energy consumption exceeds the battery capacity, the action is ignored.
- \(\delta_{E(j, t + T_{i,j,t}^a) + E^e_{i,j,t}}\) is the delta function, which returns 1 when \(E(j, t + T_{i,j,t}^a) + E^e_{i,j,t}\) is less or equal than battery capacity, otherwise returns 0. The function is used to constrain the action by the current energy level. If the state requires more energy than the battery can provide, the state is infeasible. For ICE taxis, the function always returns 1.
- \(E^e_{i,j,t}\) is the energy to move the vehicle from junction \(i\) to junction \(j\) at time \(t\). The parameter will be discussed in the later section.
- \(U\) is the energy unit price. We use 20 cent/kWh for utility and 2.5 USD/gallon for gasoline.

The expected energy consumption \(E^a(S, A_{i,j})\) is given as follows:

\[
E^a(S, A_{i,j}) = (1 - P^p_{j,t+T_{i,j,t}^a}) E(j, t + T_{i,j,t}^a) + \sum_{k=1}^{J.alt} P^p_{j,t+T_{i,j,t}^a} P^d_{j,k,t+T_{i,j,t}^a} \left( E^e_{i,j,t} + E^a_k + E(k, t + T_{i,j,t}^a + T_{j,k,t+T_{i,j,t}^a}^t) \right) + E^e_{i,j,t}
\]

where \(E^e_k\) is the minimum required energy for the EV to move to the nearest charging station in junction \(k\), which will be discussed in Sec.5. The optimal policy \(\pi\) is defined as follows:

\[
\pi(S) = \arg \max_{A_{i,j}} \left( R^a(S, A_{i,j}) \right)
\]

where \(R(S) = R^a(S, \pi(S))\) and \(E(S) = E^a(S, \pi(S))\).

5 MARKOV DECISION PROCESS PARAMETERS

We describe the details of the essential parameters of the MDP model in this section. In this study we use the taxi trip dataset on January 16 2013.

5.1 Traffic Speed Network

There are two objectives of traffic speed network construction:

1. Estimate the idling time (e.g., when the taxi stops moving due to red light and traffic), which is an essential factor for calculating the taxi fare.
2. Utilize the driving speeds in road network to compute the energy consumption of the taxi.

Travel time is a time-dependent parameter, since it is highly affected by traffic condition. For example, the travel time between the same pair of junction \(i\) and junction \(j\) will be higher in the office hour and much lower at the midnight.

The first step of constructing the traffic speed network is to determine the driving path of the taxi. We use Spatialite [3] to calculate the shortest path for each pick-up and drop-off locations. Spatialite utilizes OpenStreetMap (OSM) data to determine the shortest path. The resulting path comprises a list of edges (segments) described by two junctions. We then compare the record distance to the computed distance. If the difference between the record and the path length is greater than 300 meters, the record is discarded since the driver is likely to take other route. For each computed path, the segments of the path are labeled with the average speed using record travel time and distance. We enumerate all data within one-hour time slot to find a list of average speeds for segment. The highest speed is selected to represent the travel speed of the edge, since it is the observed highest speed without stopping.

Given the travel speed network, we can estimate the driving time from the network. Therefore, the idling time is estimated by subtracting estimated driving time from record travel time. The steps for calculating the idling time are described below:

1. Average travel time \(T_{i,j,1}^t\): There may be several trips start from junction \(i\) to junction \(j\), however, their travel times are slightly different. We average the travel time of the same trips.
2. Driving time \(T_{i,j,1}^d\): The shortest path from junction \(i\) to junction \(j\) is determined by Spatialite. Then driving time in
We denote the passenger destination probability from junction \( i \) by the number of total trips starting from that junction. From the record taxi trip data, we can calculate the idling time ratio of each record:

\[
\lambda = \frac{T_{i,j,t}}{T_{i,j,t} + \bar{d}_{i,j,t}} \quad (4)
\]

We denote \( \bar{d}_{i,j,t} \) as the median idling ratio in the distribution of idling time ratio between time 9:00 to 10:00 AM. We observe that, in median, 72% of the travel time is used in idling. In Fig.2b, only 40% of travel time is used for idling between 3:00 to 4:00 AM due to less traffic condition.

### 5.2 Passenger Pick-up Probability \( P_{i,t}^p \)

Passenger pick-up probability describes the chance of a taxi driver can pick up passengers at junction \( i \) at time \( t \). We consider the number of taxis around the junction and the pick up record of the junction to calculate the pick-up probability in 3-minute time slot.

(1) For a junction \( i \) from time \( t \) to \( t + 3 \), we denote the number of all pick-up events at the junction by \( n_{i,t,t+3}^p \).

(2) To estimate the number of taxis around the junction in 3 minute time slot, we denote the number of all drop-off events from time \( t - 3 \) to \( t + 3 \) within 300 meters distance from the junction by \( n_{i,t-3,t+3}^d \). We assume the taxis are vacant after drop off passengers and may roam to the junction \( i \) within 300 meters in 3 minute.

Therefore, the passenger pick-up probability is computed as:

\[
P_{i,t}^p = \frac{n_{i,t,t+3}^p}{n_{i,t,t+3}^p + n_{i,t-3,t+3}^d} \quad (5)
\]

### 5.3 Passenger Destination Probability \( P_{i,j,t}^d \)

Passenger destination probability describes the chance that passengers transfer from one junction to another. This probability is time-dependent. For example, passengers are more likely to move from their homes to offices in working hours. We use one hour time slot to construct passenger destination probability in this paper.

In each time slot, we calculate the number of trips between each junction and its successors. Then we normalize the number of each junction by the number of total trips starting from that junction. We denote the passenger destination probability from junction \( i \) to junction \( j \) at time \( t \) as \( P_{i,j,t}^d \).

### 5.4 Energy Consumption of EVs \( E_{i,j,t}^e \)

We use a blackbox method to construct energy consumption model for the EV [2, 8]. The energy model is based on the average driving speed and auxiliary loading. The total energy consumption can be simply decomposed into moving energy consumption and auxiliary loading energy consumption:

\[
E_{i,j,t}^e = E_{i,j,t}^{mv} + E_{i,j,t}^{ax} \quad (6)
\]

#### 5.5 Minimum Required Energy \( E_{i}^{min} \)

The electric taxis should arrive at each junction with the minimum SoC, which guarantees them to reach the nearest charging station without strand. We use New York charging stations data from [4]. In general, there are two types of charging stations, one for Tesla and another support various kinds of EVs. We notice that there are other charging stations require registered memberships or payments, thus are not considered in this study.

To compute the minimum required energy \( E_{i}^{min} \) to the nearest charging station in junction \( i \), the minimum distance between the junction and the nearest charging station is utilized. The steps are listed below:

(1) We utilize Spatialite to determine the nearest charging station \( g \) for each junction \( i \) in the road network by the shortest distance \( D_{i,g} \).

(2) The shortest distance is converted into the required driving time using the traffic speed network.

(3) The median idling ratio \( \bar{\lambda} \) is used to calculate the idling time.

(4) Given \( D_{i,g} \), driving time and idling time, the required energy \( E_{i}^{min} \) is calculated by Eq.6.

#### 5.6 Taxi Profit of Trip \( F_{i,j,t} \)

We use the fare rule for New York taxi to calculate the fare. Since there are different kinds of surcharge based on times and days, the fare is time-dependent. The general rules are listed below:

- The initial charge is $2.50.
- Plus 50 cents per 1/5 mile or 50 cents per 60 seconds in slow traffic or when the taxi is stopped.
- There is a 50-cent MTA State Surcharge for all trips that end in New York City or Nassau, Suffolk, Westchester, Rockland, Dutchess, Orange or Putnam Counties.
- There is a 30-cent Improvement Surcharge.
- There is a daily 50-cent surcharge from 8pm to 6am.
- There is a $1 surcharge from 4pm to 8pm on weekdays, excluding holidays.
- Passengers must pay all bridge and tunnel tolls.

We ignore toll fees since the taxi driver will not receive any profit from tolls. The profit of a trip can be calculated by deducting fuel/electricity cost from the revenue. Therefore, the profit of a trip from junction \( i \) to junction \( j \) at time \( t \) is as follows:

\[
F_{i,j,t} = 2.5 + \frac{D_{i,j}}{1.60934} - 2.5 + \frac{T_{i,j,t}}{60} \cdot 0.5 + Q_1 - E_{i,j,t}^e \cdot U \quad (9)
\]

where
We use NYC taxi trip dataset to evaluate the MDP for conventional ICE taxis. The refueling or charging decisions are not considered in the simulation. We present the results based on NYC taxi trip dataset on January 16 2013. Most NYC taxis have two shifts per day, each shift is 12-hour long. The taxi drivers usually change the shift from 4 to 5 AM. In this study, we analyze the taxi profit in the morning shift, e.g., 4 AM to 4 PM.

In this section, we apply the optimal policy of MDP to only one taxi driver, while assuming the behaviors of other taxi drivers remain the same as in the dataset.

Fig.3a shows the distribution of taxi profits from the trips of 11992 taxis in the morning shift. Since we do not have roaming traces of taxis when the passengers are dropped off, the profit from the trips can be seen as the profit upper bound. The blue line displays the profit boundary of 50% taxi drivers (e.g., the median of the distribution). We observe that 50% drivers earn above USD$186. The red line depicts the expected profit when the taxi driver follow the optimal policy of MDP. The taxi driver is expected to obtain USD$374 profit following the optimal policy. The result shows that the policy enables the driver to earn among top 0.1% in the morning shift. Fig.3b depicts the distance of transporting passengers. Above 50% taxis drive more than 55.8 kilometers to transport the passenger in the day. By following the optimal policy, the taxi driver is expected to drive 119 kilometers to transport passengers. Although the expected driving distance is 0.37%, the profit is ranked 0.1%. The reason is that the profit is not linear proportional to the driving distance of transporting passengers, it depends on fuel cost, number of trips and idling time.

7 CASE STUDY
7.1 Profitability Analysis of ICE Taxis
We use NYC taxi trip dataset to evaluate the MDP for conventional ICE taxis. The refueling or charging decisions are not considered in the simulation. We present the results based on NYC taxi trip dataset on January 16 2013. Most NYC taxis have two shifts per day, each shift is 12-hour long. The taxi drivers usually change the shift from 4 to 5 AM. In this study, we analyze the taxi profit in the morning shift, e.g., 4 AM to 4 PM.

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7.2 Profitability Analysis of Electric Taxis
We consider the energy consumption model of Nissan Leaf to simulate the MDP using different battery capacities. There are Nissan Leaf with 24 or 30 kWh battery. Usually, the EVs will not be fully charged to protect the battery. Leaf will stop being charged when the State-of-Charge (SoC) of battery reaches 95%. Therefore, 95% battery capacity is available in the simulations.

Fig.4a depicts the results of the profits obtained by Leaf with different battery capacities on the same day. The bar shows the operating time of Leaf when the battery is depleted. There are some observations:

- Leaf equipped with 30 kWh battery will deplete the battery around 8 hours. The driver will get expected USD$289 profit following the optimal policy. However, there are 4 hours remain in the shift, the driver is expected to earn more than this if charging the taxi for a short period.

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**Algorithm 1. SolveMDP**

1: for \( t = t_{\text{end}} \) to 1 do
2: for each node \( i \in \text{Network} \) do
3: \( J \leftarrow \text{getSuccessor}(i) \)
4: for each node \( j \in J \) do
5: \( A_{\text{max}} \leftarrow A \) that maximizes \( R^*(S, A) \)
6: \( \pi(S) \leftarrow A_{\text{max}} \)
7: \( R(S) \leftarrow R^*(S, A) \)
8: \( E(S) \leftarrow E^*(S, A) \)
9: end for
10: end for
11: end for
12: return \( \pi(S) \)

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**Figure 2:** Hourly distribution of idling ratio and median idling ratio over a day.

- \( D_{ij} \) is the route distance between junction \( i \) and junction \( j \) and the unit is kilometer.
- \( Q_t \) is the surcharge according to time \( t \).
- \( U \) is the energy unit price. We use 20 cent/kWh for utility and 2.5 USD/gallon for gasoline.

**Figure 3:** Distributions of taxi profit upper bound and driving distance of transporting passengers.

- \( \lambda \) is the idling ratio.
- The red line depicts the expected profit when the taxi driver follows the optimal policy of MDP. The taxi driver is expected to earn among top 0.1% in the morning shift.
The maximum expected profit is USD$386 when battery capacity is above 50 kWh. The profit is higher than ICE taxis (as benchmark) since the electricity cost is cheaper.

- The profit improves not much when battery capacity increases from 40 to 50 kWh due to less pick-up events around 4 to 5 AM.

Fig 4b shows the results of expected transporting distance and searching distance of different battery capacities. There are some observations:

- Leaf equipped with 30 kWh battery is expected to drive 136 kilometers consuming 27.6 kWh. A portion of energy is reserved for going to nearest charging station.
- The taxi is expected to drive 229 kilometers including searching and transporting to achieve maximal profit. The expected energy consumption is 45 kWh.

Fig. 4b shows the results of expected transporting distance and energy consumptions of different battery capacities.

The essential parameters in the model are inferred from the historical taxi trip dataset. The optimal policy allows the driver to obtain the profit above 99.9% drivers. To achieve comparable profit with conventional taxi driver, at least 45 kWh battery capacity for Nissan Leaf is required. The maximal profit by electric taxi is 3% higher than that of conventional taxi in the morning shift given sufficient battery capacity. The expected profit of existing Nissan Leaf model is able to achieve higher than 50% conventional taxi without charging following the optimal policy. An extended technical report can be found at [7].

8 CONCLUSION

In this paper, we use Markov Decision Process to model the taxi service strategy and determine the optimal policy for taxi drivers.

REFERENCES