Indian Institute of Information Technology Vadodara

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Design Project Report-2021

on

Optimal Routing of Electric Vehicles in Networks with Charging Nodes

Submitted by

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Abstract-Motivated by the significant role of recharging in battery-powered vehicles, we study the routing problem for vehicles with limited energy through a network of charging nodes. We seek to minimize the total elapsed time for vehicles to reach their destinations considering both traveling and recharging times at nodes when the vehicles do not have adequate energy for the entire journey .We have solved this problem using two separate approaches Node based and spatial domain based approach. In node based we have used the concept of backtracking and using various data structures and used the different graph for the implementation of the network of the Charging station in a particular city and used the graph algorithms to solve the query of the electric vehicle ev-routing and have produced the best result for the multi user and tried to save the time and energy of the user as much as we can and produced the best results. In spatial domain based approach we have used location features of places along with various factors affecting route like traffic, population density etc to find optimal CS using reinforcement learning..

I INTRODUCTION

Since they were introduced more than 100 years ago, electric vehicles are seeing a resurgence in popularity for many of the same reasons they were first popular.It may come as a surprise to many that the EV, the craze today, is not a recent innovation.While history is uncertain about who actually created the very first EV, what is certain is that there were electric motors in use as far back as the early 1800s. One known electric motor was created in 1828 by Anyos Jedlik . He made a small model car that could move on its own via a small electric motor, and that was the spark to the new technology. In the early 1900s, American inventors returned to the EV. Around this time, William Morrison created what many consider the first practical electric car, although it still lacked range. Hybrids were also created during this time to solve a number of issues with the EV [1].

There were starts and stops of the electric vehicle industry in the second half of the 20th century and the technology was not looking promising, but due to the energy crisis and environmental pollution problem, petroleum use and energy diversity gained global attention and raised public concern in many countries [6]. This was where, true revival of electric vehicles happened around the start of the 21st century.The introduction of Electric vehicles(EV's) has been proven to reduce CO2 emissions and dependence on petroleum products.In addition to this, EV has several other advantages too, including:

Weekly trips to the gas station to fuel up your car are expensive, especially when the ever-fluctuating price of gasoline is high. By choosing an electric vehicle, you can forget about paying for gasoline and being at the mercy of gas prices. Not only is electricity less expensive than gasoline, it also has a much more stable price point, meaning that rapid price swings are all but eliminated by going electric.Electric cars run on electrically powered engines, and hence there is no need to lubricate the engines, anything related to the combustion engine or a ton of maintenance tasks that are usually associated with a gas engine. Therefore, the maintenance cost of these cars has come down. The use of electric vehicles also curbs noise pollution as they are much quieter. Electric motors are capable of providing smooth drive with higher acceleration over longer distances. They are safer to use, given their lower center of gravity which makes them much more stable on the road in case of a collision [8].

II LITERATURE SURVEY

The increasing presence of Electric Vehicles (EVs) has given rise to novel issues in classical network routing problems [1]. There are four battery powered EVs characteristics which are crucial in routing problems: limited cruising range, long charge times, sparse coverage of charging stations, and the BPV energy recuperation ability [2], which can be exploited. In recent years, the vehicle routing literature has been enriched by work aiming to accommodate these BPV characteristics. For example, by incorporating the recuperation ability of EVs, extensions to general shortest-path algorithms are proposed in [4] that address the energy-optimal routing problem. Charging times are incorporated into a multi-constrained optimal path planning problem in [3], which aims to minimize the length of an EV's route and meet constraints on total traveling time, the total time delay due to signals, total recharging time and total recharging cost.This was where, true revival of electric vehicles happened around the start of the 21st century. In [4], algorithms for several routing problems are proposed, including a single vehicle routing problem with inhomogeneously priced refueling stations for which a dynamic programming-based algorithm is proposed to find a least-cost path from source to destination. More recently, an EV Routing Problem with Time Windows and recharging stations (E-VRPTW) was proposed in [5], where controlling recharging times is circumvented by simply forcing vehicles to be always fully recharged.

III Problem statement

We consider a network of charging stations (CSs) and a set of paths connecting various CSs. The main goal is to find an optimal path that minimizes the total travelling time between the source to destination (charging station or any predefined location). Finding the optimal path depends on various factors like traffic, population density, road condition, etc.

We assume two scenarios:
Scenario 1:-If a person wants to travel from one source point(i.e. its current location or any other point) to the destination point then we will show them the most optimal path(i.e., that leads to the destination in minimum time). After finding the most optimal path, we will show the list of the charging stations to the user based on the minimum waiting time for getting the slot at the Charging station. We solve this problem using a node-based approach.

Scenario 2:- If a person only needs to get his EV charged at a nearby charging station then we find the optimal path to reach the nearby charging station. For this problem, we propose both a node-based and spatial-domain based approach.

IV PROPOSED METHODOLOGY

First Scenario

We first discuss the approach proposed for the first scenario where we want to find the optimal path between source to destination and the charging stations in that path that have less waiting time which helps to minimize the overall travel time between the source to the destination.

Node Based Approach:-

We divide our algorithm into two phases. First part of the algorithm is the generation of a network which will be used as input to our next part of the algorithm.

First Phase:- *Network Generation*
We create a network of the charging station as an undirected weighted graph i.e., $G = (N , A)$ with $N = \{1, . . . , n\}$ and $|A| = m$ where m is the number of edges in the graph and n is the number of charging stations (as nodes)). For any two nodes $i, j \in N$, if there exists $(i, j) \in A$ that means there is a path connecting node i to j. In order to do so, we follow following steps:

1. We take the input from the user the number of charging stations.
2. A unique charging station number is assigned to each node.
3. We also create a path between any two nodes and provide the weight i.e., the distance between the two nodes.
4. We maintain various queues with each charging station such as a Busy_Queue (stores the booking slots times), Next_Available_Time slot (NATS)(stores the next Available time slot).
5. We update the Busy_Queue and NATS based on requests arriving from any EVs.

Second Phase:- *Finding the optimal path using a greedy approach between source to destination.*
We design the algorithm which follows the following steps:

1. The algorithm takes a few inputs from the user such as source, destination and the remaining percentage of charge.
2. We compute the distance which can be covered by the remaining percentage of battery charge as distance_covered_with_the remaining_percent(DCRP)=(charging_percent/10).
3. We first find the shortest path from the source point to the destination path by exploring all the paths between them using the concept of recursion and backtracking. We also store the charging station information(i.e. Charging Station Number) on that path. Here, basically we have explored all the paths in the graph and also stored the total path distance of each path in a map<int,vector<int>>. We have stored the total path distance as key and value as vector containing the Charging station number we have visited in the respective path and after exploring the paths we will get the least distance path value at the top because maps have the inbuilt function of sort by key.
4. The list obtained from the above step, we try to find the charging stations that can be reached by the left out charging capacity of the EV.
5. Once we find the CSs that can be easily reached from the current battery capacity, then we check the waiting queue of the CS. The CS which has minimum waiting time will be picked and based on the information available in the Next_Available_Time slot queue, we can find the slot for charging the EV.

This way we find the optimal path from the source to destination by finding the shortest path that minimizes the travel time. Also, we find the charging stations of that path that minimizes our waiting time, which helps to minimize the total travel time and time complexity of the above algorithm is O(V^4) and the space complexity is O(V^2).

Second Scenario:- Finding the optimal path to reach the nearby charging station.
For this problem, we proposed two approaches.
Node based Approach:-We follow the following steps in this approach.

1. We take the input as source location and the % of remaining charge of the EV from the user.
2. We apply the BFS(i.e. Breadth First Traversal) from source point and find the charging stations that can be covered by the remaining charging capacity of the EV.
3. Then we find the CS that has minimum waiting time, although that may not be the shortest distance from the source.

This helps to pick the station that can enter the start time and end time and accordingly we will book them the CS and provide them with the Unique booking ID and the time complexity of this algorithm is O(V) and space complexity is O(V^2).

Spatial domain Based Approach:-

In this approach, we have implemented Reinforcement learning algorithms, Markov Decision Process[9], Dynamic Programming to find optimal CS. We first preprocessed the image, in which we used tiles of 20*20 and divide image into grid of 50*50. For each grid cell we filled with the mean value of tile(Fig:- 1.b). Here calculating euclidean distance is not a good representation of actual distance between locations.(Fig:- 1.d) So somehow we have to give the information of path(i.e. roads) and non-path(like houses, apartments etc). So for this we used Reinforcement Learning in which we assigned some reward for each cell/state(for path: -1 and for non-path: -10).

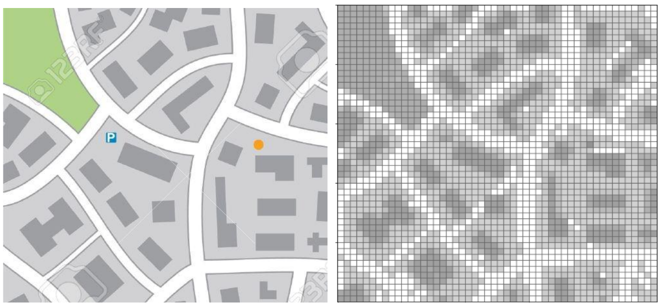


Fig: 1.a , 1.b

Here we define two types of rewards.

- Short term reward a.k.a reward
- Long term reward a.k.a. Return or value function[9]

$$v_\pi(s) \doteq \mathbb{E}_\pi\left[G_{tt} = s\right] = \mathbb{E}_{\pi k=0}^{\infty}\gamma^k R_{t+k+1} \mid S_t = s, \text{ for all } s \in \mathcal{S}$$

Calculating the value function of all future paths is not tractable(Fig:- B). For this we use the Bellman equation[9] for state-value and action value function.

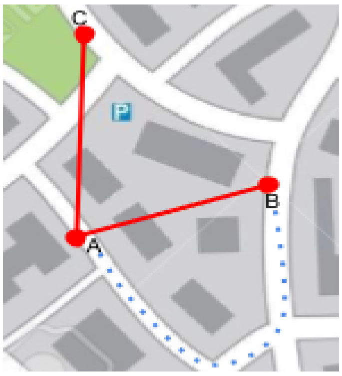


Fig:- 1.c

Here we define cumulative future reward/Return because short term reward is not enough to make optimal choices like here in figure: 1.d from initial pos both choice 1 and choice 2 have short term reward of -1(because on the path) but Choice one is better because it is closer to destination.

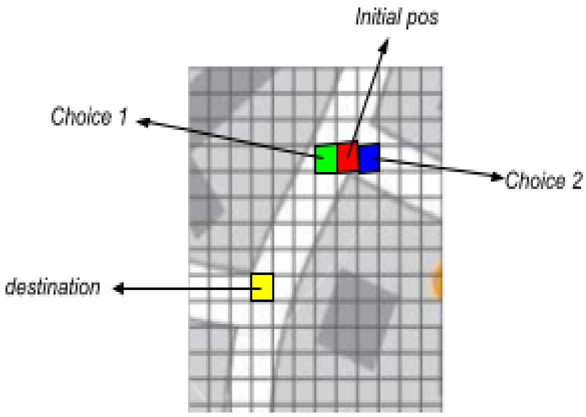


Fig:- 1.d

Derivations:-

State-value function

$$\begin{aligned} v_\pi(s) &\doteq \mathbb{E}_\pi\left[G_t \mid S_t = s\right] \\ &= \mathbb{E}_\pi\left[R_{t+1} + \gamma G_{t+1} \mid S_t = s\right] \\ &= \sum_a \pi(a \mid s) \sum_{s'} \sum_r p\left(s', r \mid s, a\right)\left[r + \gamma \mathbb{E}_\pi\left[G_{t+1t+1} = s'\right]\right] \\ &= \sum_a \pi(a \mid s) \sum_{s', r} p\left(s', r \mid s, a\right)\left[r +_\pi\left(s'\right)\right], \quad \text{for all } s \in \mathcal{S}, \end{aligned}$$

Action-value function

$$\begin{aligned} q_*(s, a) &= \mathbb{E}\left[R_{t+1} + \gamma \max_{a'} q_*\left(S_{t+1}, a'\right) \mid S_t = s, A_t = a\right] \\ &= \sum_{s', r} p\left(s', r \mid s, a\right)\left[r + \gamma \max_{a'} q_*\left(s', a'\right)\right] \end{aligned}$$

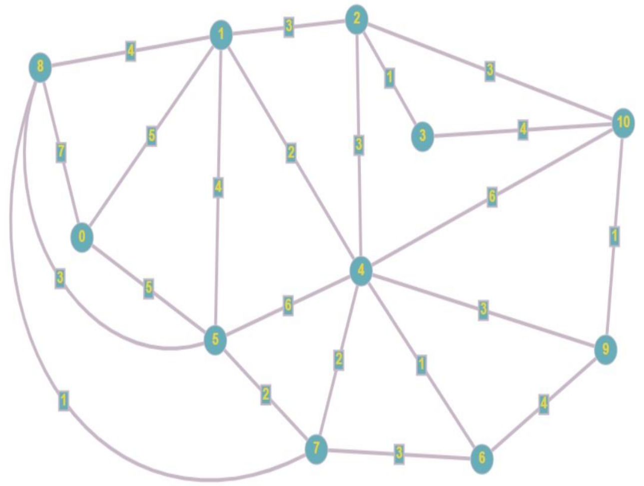
Here we will have k linear equations in k variables where these k variables are the value function of k states. Our image has 2500 states and solving it is computationally heavy. So for this we will use Dynamic programming with the Bellman equation as an update rule:

$$v_{k+1}(s) \doteq \mathbb{E}_\pi \left[R_{t+1} +_k (S_{t+1}) \mid S_t = s \right]$$
$$= \sum_a \pi(a \mid s) \sum_{s',r} p(s', r \mid s, a) \left[r + \gamma v_k(s') \right]$$

We have implemented this algorithm from scratch using python, numpy and for plotting graphs and maps we have used opencv and matplotlib.

V RESULT AND DISCUSSION

Node-Based Approach:-



The above figure shows the network of Charging stations in a city and results are written inside the table on the basis of this network.
1:-Speed of the car is 10 km/hr(Assumption) and in one full charge it can travel only 10km

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No.	Source(S)	Destination(D)	Percentage of remaining battery	Path Length	CS between S to D	CS till where EV can reach depending upon the remaining percentage	Rearranged the CS on the basis of Waiting time(Waiting time of each station)	Booking Charging Station Number	Station till which you reach after getting fully charged	Total travelling time=total waiting time+travelling time.
1	0	9	90	10	0->1->4->9	0->1->4	0(0)->1(0)->4(0)	0	9	0+1=1
2	0	9	80	10	0->1->4	0->1->4	1(0)->4(0)->0(1)	1	9	0+1=1
3	0	10	20	11	0->1->2->10	0	0(1)	0	2	1+(8/10)+0+(3/10)=2.1
	2	10	20	3	2->10	2	2(0)	2	10	
4	8	10	40	7	8->7->4->9->10	8->7->4	8(0)->7(0)->4(0)	8	10	0+(7/10)=0.7

In the 1st and 2nd and 4th case we will reach the destination after charging only one time in between the journey.

In 3rd case EV needs to get it charged for two times to complete its total journey and we can see that after charging first time we will only reach one of the intermediate CS and after that we will consider the last reachable station as source point and the destination point remains the same and then the same algorithm will suggest the CS for charging.

2.When we consider that only we need to get our EV charged at any nearest charging station.

S.no.	Source	Battery Percentage	Nearby Charging Station till where we can reach	Rearranged CS number(Waiting time) on the basis of waiting time.	Booked Charging station
1	0	60	0->5->1	5(0)->1(1)->0(2)	5
2.	5	40	5->7->8->1->4	7(0)->8(0)->4(0)->1(1)->5(1)	7
3	8	20	8->7	8(0)->7(1)	8
4	4	90	4->6->7->1->9->2->8->10->5->3->0	4(0)->6(0)->9(0)->10(0)->3(0)->2(1)->5(1)->7(1)->8(2)->1(1)->0(2)	4
5	2	10	2->3	3(0)->2(1)	3

Spatial-Domain Based Approach

Test Case 1:-
In this test we find the optimal path from source to destination. First we set our Destination CS and source(Fig:1.e). After this the algorithm finds the optimal path from source to destination(Fig:1.f). We can see the heatmap of the value function generated by our algorithm (Fig:1.g). This heatmap is brightest at the location of the destination CS which shows it is optimized.

Fig:-1.e

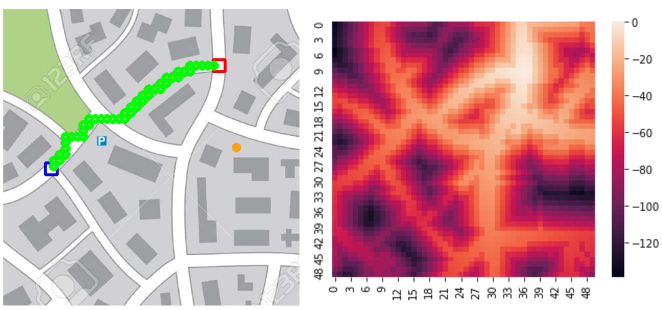

Fig:- 1.f, 1.g

Next we repeat the same process but by blocking a path(Fig: 1.h). Due to this a new optimal path is found(fig:1.h). Now due to this the whole map left of this blocked region is darkened in the value function heatmap(1.i).

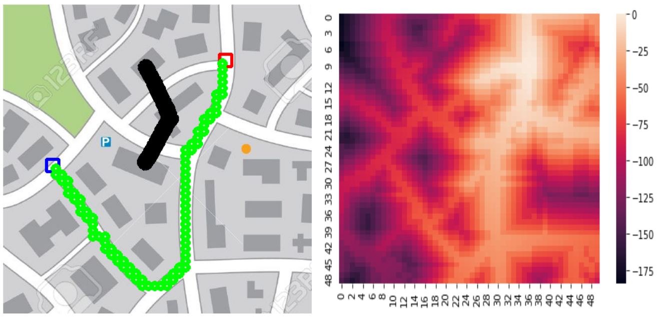

Fig:- 1.h, 1.i

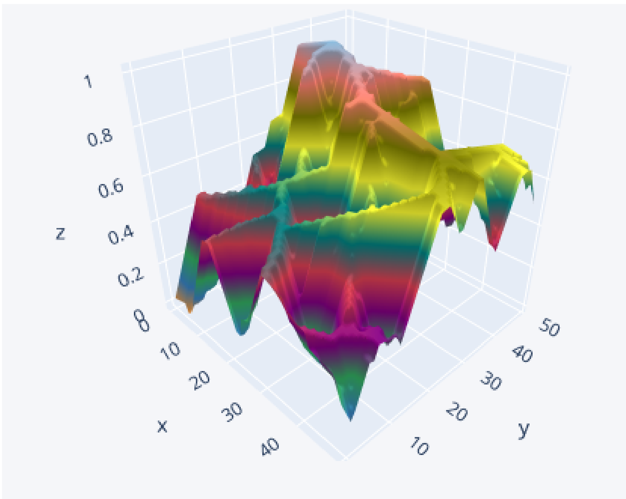

Fig:- 1.j

Fig:- 1.j shows the 3d representation of our value function. We see there is only one peak(blue in color) at the location of destination CS and there is no smaller peak which implies that no matter where we are on the map we will reach this destination CS in an optimal way.

Test Case 2:-

In this test we have 3 CS(red squares) and 1 Source(blue square) . Our algorithm finds the route which takes the shortest time and leads us to one of the CS. In this case the 3d plot of the value function will have 3 peaks corresponding to 3 CS (fig: 2.b)

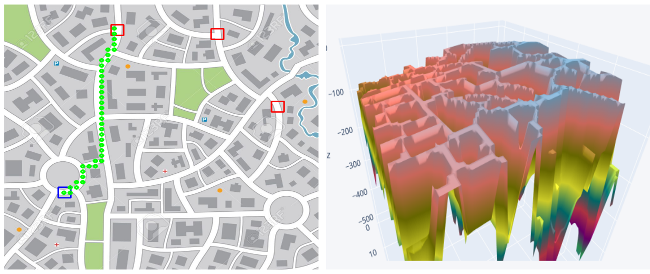

Fig:- 2a, 2b

Test Case 3:-

Here we have created some artificial data of traffic, road condition, population density etc to see its effect on our path(Fig:3.a). We see our input matrix(Fig: 3.b) is also accounting for this data i.e., in the original image(Fig: 3a) where we have some traffic, corresponding to that point the reward is -7 in reward matrix(violet color patches on our heatmap Fig: 3.b).

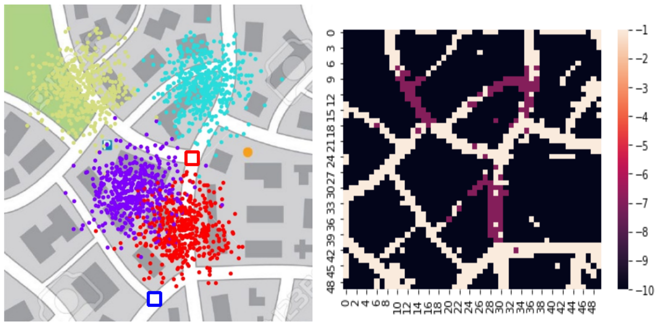

Fig:- 3a,3b

Now our new path is created (Fig:- 3.c) avoiding the traffic. This new path may not be the shortest path but it ensures the shortest travel time and thus is optimal.

Fig:- 3c

VI CONCLUSIONS AND FUTURE WORK

After doing this project we can conclude that it was very much informative and helped us to apply our knowledge on upcoming challenges for the upcoming idea of EV adaptation and we will in future develop this project with a better UI and we will also work upon the efficiency of the en-routing algorithm.For the spatial algorithm we are planning to use real map data like terrain map or live satellite images using some Google map API, along with the real time traffic data.

Using spatial domain has many benefits in EV enrouting. This makes interpretation of our problem statement very easy. Like here we can directly correlate the reward of each state with the time required to travel that grid unit. Since the feature is location based so we can use the GPS location of each car to know which grid cell takes how much time to travel, we simply pass that time as the reward to our algorithm and this gives a very accurate prediction of travel time which will be very close to actual travel time. We found optimal CS locations by simply minimizing total travel time for each point on our map. Since, we considered 50*50 matrix, we can pass it into the ML model and make predictions about how traffic grows. This tells us about any traffic Jam even before it is created, thus it helps to avoid it by selecting another route. We will extend this work to solve the same problem with other constraints like remaining battery capacity, traffic in CS, etc. and also explore the routing problem for multiple EVs.

VII ACKNOWLEDGMENT

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