Optimal Electric Vehicles Route Planning with Traffic Flow Prediction and Real-Time Traffic Incidents

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Abstract: **Electric Vehicles (EVs) are regarded to be among the most environmentally and economically efficient transportation solutions. However, barriers and range limitations hinder this technology's progress and deployment. In this paper, we examine EV route planning to derive optimal routes considering energy consumption by analyzing historical trajectory data. More specifically, we propose a novel approach for EV route planning that considers real-time traffic incidents, road topology, charging station locations during battery failure, and finally, traffic flow prediction extracted from historical trajectory data to generate energy maps. Our approach consists of four phases: the off-line phase which aims to build the energy graph, the application of the A* algorithm to deliver the optimal EV path, the NEAT trajectory clustering which aims to produce dense trajectory clusters for a given period of the day, and finally, the on-line phase based on our algorithm to plan an optimal EV path based on real traffic incidents, dense trajectory clusters, road topology information, vehicle characteristics, and charging station locations. We set up experiments on real cases to establish the optimal route for electric cars, demonstrating the effectiveness and efficiency of our proposed algorithm.**

Keywords: **Electric Vehicles, dynamic route planning, A*, real-time incidents.**

I. INTRODUCTION

An increasing variety of sensors and computing devices are ubiquitous embedded in our daily living environments, such as GPS devices (e.g., in-car navigation applications and smartphones) and RFID tags (e.g., Electronic toll systems and e-rate cards). Consequently, a large amount of information concerning mobility behaviour and trajectories data becomes widely available. With this wealth of data, new opportunities are opening up to conduct more sophisticated and deeper analysis for transport system design, planning, and management [1].

Trajectory data provides detailed information regarding moving objects including their activities, speed, most visited locations, and their preferred trajectories [2]. The collection and analysis of massive spatio-temporal trajectory data affords an unprecedented opportunity to forecast human mobility, future tourist locations, and traffic control in road networks. It allows discovering the interactions amongst moving objects, gaining knowledge about moving group patterns and specifying the location of specific objects or services. In this article, we focus on studying the route planning domain which is considered as one of the most active areas where trajectory data have been used to improve the daily movements of thousands of users all over the world. In particular, we are interested in exploring optimal routes for electric vehicles.

Electric vehicles (EVs) have been identified as a significant technical orientation to reduce cars' emission and energy-saving promotion [3]. According to the annual publication of the Global EV Outlook, which collects and reviews the latest trends in electric mobility worldwide, global sales of EVs surpassed 2.1 million in 2019, exceeding 2018, which was already a peak year, to raise the stock to 7.2 million EVs [4].

Electric Vehicle utilization has risen significantly over the 21st century as global energy needs have shifted away from fossil fuels. The widespread market penetration of EVs introduces new challenges to traditional operations within the electric system [5].

However, the EVs restricted range, as well as their long battery charge duration, represents serious constraints to their widespread adoption. Besides, long-distances trips need careful planning to identify appropriate charging stations to prevent energy shortages [5]. Therefore, drivers are most interested in finding sustainable solutions to reduce their energy consumption.

Existing navigation systems, such as Google Maps, Waze, and MapQuest, have been developed to improve the path planning domain. Unfortunately, they provide routes that only take into account certain types of travel costs such as time and length. They don't consider the specificity of electric cars and the factors that influence their energy consumption. Thus, such road recommendations are not suitable for Electric Vehicles [6].

Some recent research on Electric Vehicle has focused on understanding and identifying the factors that influence the energy consumption of EVs, such as drivers' vehicle characteristics [7], traffic congestion [8] and speed in motion [9]. Therefore, there is an important focus on route planning and travel recommendation to better select an optimal route with lower energy consumption, particularly for an EV with limited battery capacity. However, most of this work does not take into account simultaneously all the factors influencing energy consumption. In this paper, we intend to minimize the energy consumption of electric cars by providing an optimal route planning approach that includes a static prediction depending on the characteristics of the road affecting EVs battery such as road topology and traffic flow prediction extracted from trajectories data. Besides, our approach includes a real-time update that takes into account route state and real-time traffic incidents. It also provides the available charging station in case of a battery drop.

This paper is organized as follows. In Section 2, we present the literature review and a description of our problem. Section 3 presents our approach and outlines its different phases. The implementation of our contribution and the simulation of results are described in Section 4. Finally, Section 5 concludes the paper with some remarks and perspectives.

II. LITERATURE REVIEW

Standard route planning deals mainly with the shortest route issue, whereby the best path needs to be found from the origin to the destination depending on certain criteria. Generally, either travel time (the fastest path), travel distance (the shortest path), energy consumption (the economical path), or a combination of these criteria are considered to be optimized.

Electric vehicle usage has raised many challenges in application areas associated with transportation and green logistics as well as with vehicle routing issues in general. Below, we offer the latest literature reviews on EVs' energy consumption route planning. Planning itineraries, for minimizing fuel consumption, involves different constraints and factors impacting energy use. This was introduced first by [10] when integrating battery constraints into the Dijkstra algorithm, and then adapting acceleration methods for rapid queries, followed by [11] that also developed the potential shift method to address the negative edge costs problem. Besides, battery drops were considered in [12] but they did not include the waiting time at the charging station nor the charging time. Although, several studies focused on finding optimal routes regarding the charging station location, recharging time [13, 14], and waiting time at the charging station [6].

Various extensions of the Electric Vehicle Route Planning have been studied by considering the trip time for EVs. [15] and [16] explored the fastest feasible routes while minimizing the overall trip time on road networks. [16] used a multicriteria version of Dijkstra's algorithm on a multi-graph with edge weights that represent several time-consumption trade-offs. Besides, in [15], an approach (CHArge) that enables the computation of optimal routes while handling all types of stations was proposed. [17] presented a multi-criterion shortest-path search to find the best compromise between the fastest and most economic route, taking into account the advantages of driving below the speed limit for energy-saving.

Further research addressed EV recharging constraints. [18] studied possibilities of partial recharging at the charging station through a formalism called "state of charge". [19] developed a new trip planner that takes a broader, multi-destinations perspective for EV route planning and EV recharging that meets EVs' needs in a way that also reflects charge availability. [20] considered the impact of EV recharging on power quality in the distribution network and suggested an optimal browsing strategy to quickly recharging, using the Internet of Things.

Studies were carried out to develop techniques for EV fleet route optimization. Approaches such as [21, 22] focused on minimizing the waiting time of EV taxi fleets. In addition, different factors that affect EV energy consumption were also discussed. We can cite the road gradient effect [23, 24] which has a linear impact on fuel usage, and the effect of ambient temperature [25, 26] affecting EV battery capacity linearly between 15C and 20C. An approach that considered both geographical and temperature factors was proposed in [27], estimating optimal routes and their duration. The optimal hybrid vehicle driving mode and the gas-optimized route planning algorithm were provided in [16]. Further research also addressed speed planning to trade driving speed for fuel savings [28, 29]. These studies were based on exact and heuristic methods, allowing good query times after the input network pre-processing.

Considering the traffic flow, [30] developed a trajectory planning and charge navigation strategy for EVs and created dynamic traffic networks, distribution networks, and single EV models. With their approach, the optimal path can be successfully recommended and can be applied as a navigation algorithm for route planning and charging station guidance.

A combination of the above factors was studied in the literature. Sarker et al. [31] proposed a pervasive data-based route planner that takes into account range anxiety, fuel consumption, journey time, and the monetary cost of charging EVs [32]. In [19], a multi-destination route planning approach was developed considering an individual's daily requirements and charging station availability. Alizadeh et al. [33] addressed route selection, along with its charging locations and dynamic location-based electricity pricing, as well as the related charge amount under time-varying traffic conditions. Furthermore, the travel time, traffic conditions, energy consumption, and route length were considered in [34]. Besides, the approach studied in [35] discussed the impacts of personal driving behaviours and physical characteristics like traffic lights, road network topology and stop signs.

Previous researches failed to take into account real-time traffic incidents that help to avoid blocked routes. Some EVs routing approaches ignored the trajectory data analysis which is able to predict the traffic jams in the road network. We are interested in discovering efficient optimal routes for electric cars based on multiple travel costs. Drivers who prefer selecting highways won't help to gain a lot of time or distance, so they may need to plan their trip for more efficiency. Electric car drivers also have to avoid steep gradients like hilly terrain or mountains and areas known for heavy traffic.

To overcome the above challenges, alternative routes have to be studied. Routes facing a lot of stops or difficult elevations may be less efficient. So it is important to pick a route (primary route, secondary route, highways) with gentle gradients and soft traffic conditions.

Generally, the driver is the primary cause of reducing electric car range due to its stress, poor driving skills and habits, and the lack of concentration in such a situation. This behavior results in energy-waste.

With the fast growth of usage of GPS devices, smartphones and cars equipped with GPS systems, driver trajectory data became available. These useful data are very important when used to predict the traffic flow among the road network. This is a very important challenge for Electric Vehicles when facing congested routes that may ruin the battery's capacity.

The aim of this work is to study and propose a new approach for computing the optimal path for EVs taking into consideration historical trajectory data that highlight road network topology information (elevation, speed) and charging stations' location in a road network. A static prediction of traffic flow extracted from trajectory data is considered combined with real-time traffic incidents prediction that helps to identify blocked routes. At query time, an energy graph for electric cars is constructed based on those parameters.

III. EVs ROUTE PLANNING BASED TRAFFIC PREDICTION

Existing navigation systems are commonly used applications across a large range of fields. These systems, however, cannot handle the entire travel cost, so they generally provide the same path that minimizes one or two travel costs, either shortest routes or fastest routes for all drivers.

However, the derivation of the fastest or shortest route is not often the most effective way to preserve the energy consumption of EVs. Electric Vehicle drivers also need to avoid steep slopes like hilly terrain or mountains and areas known for heavy traffic. Therefore, alternative routes should be explored. A route with frequent starts and stops or difficult gradients can exhaust the battery capacity [36]. For this reason, a route with gentle slopes and traffic conditions should be chosen, taking into account the charging station's location in case of a battery drop.

To address these limitations, we propose a route planning algorithm for electric cars. It follows four steps: energy graph model elaboration, pathfinding, trajectory clustering, and path selection. This approach is performed using real-time traffic incidents and expected traffic flows between road segments based on the grouping of trajectories. We aim to reduce the EV's energy consumption by selecting an energy graph. This graph is constructed based on the characteristics of the electric vehicle and the information on the topology of the road network (length, elevation, and speed limit) to capture the actual energy consumption of each edge in the graph. In the following, we present the different steps and algorithms considered in our approach.

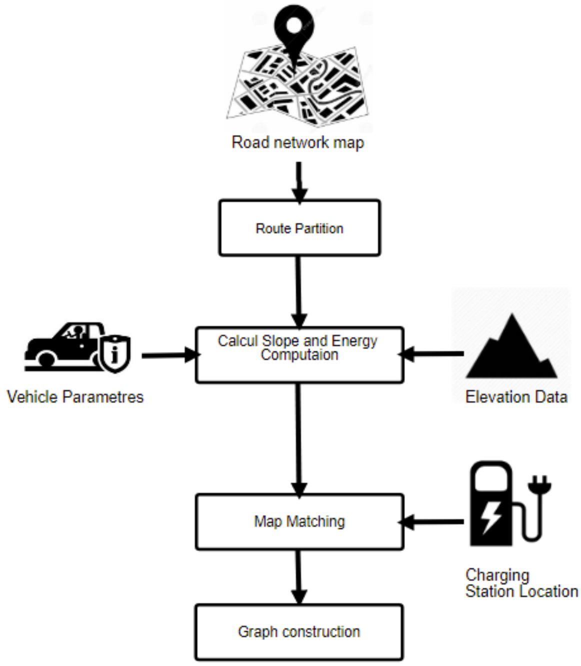


Fig 1. The off-line phase

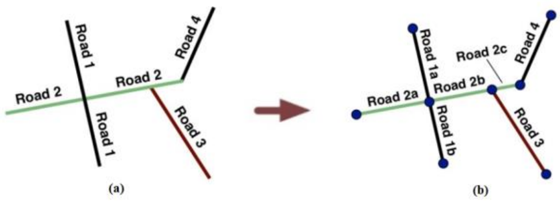


Fig 2. Road Segmentation [37]

A. *First Step: Energy graph model elaboration*

During the off-line phase, we construct the energy graph. This phase regroups several steps starting with the selection of the road map, the road network partition, the energy cost computation, the charging station integration and finally the energy graph construction. Figure 1 presents the different steps of this phase which are explained, next, in details.

1) *The route partition*

This process consists of selecting a road network map of a concerned region. The road network will be divided into road segments. This phase is performed using a standard segmentation technique which consists of splitting a road at each point where it touches or crosses another road [37] as presented in Figure 2. Figure 2a illustrates the road network before segmentation which contains 4 roads. Road 2 crosses road 1 and touches the two other roads 3 and 4. The process of splitting presented in Figure 2b gives rise to a set of road segments preserving their shapes and their belonging to the road they are part of. The goal of this process is to identify each road segment in the road network to prepare them for the next phase.

2) *The Slope Calculation*

The road topology is one of the main factors that should be considered dealing with EVs energy consumption (e.g hilly regions exhaust the battery capacity) [38, 39]. For this reason, we attempt to calculate the slope of each road segment. This phase can identify segments in the road network with heavy inclination. We assign for each node an altitude value H and for each edge$_{ij}$ its length D_{ij}. The road inclination angle σ_{ij} is calculated using the distance D_{ij} and the difference in altitude H_i and H_j between the two nodes of the segment i and j. This can be calculated as in (1).

$$\sigma_{ij} = arcsin(\frac{H_j - H_i}{D_{IJ}}) \qquad (1) \quad (1)$$

This formula returns the gradient angle of the road segment that is used next to calculate the energy cost for the segment. We focus on selecting the more representative elevation data based on the exact geographic information to assign the correct value for both nodes of the segment.

3) The energy cost computation

This phase consists in determining the segments' energy costs. We pick up a realistic model of the energy computation for commercial EVs for transporting goods, proposed by [23]. An equation based on two main factors, the road network topology (road grade, distance, speed limit) and the vehicle's parameters (speed, weight, and the frontal surface) was proposed. The reason to choose this model is that it takes into account the average speed of the road network during the journey with the driving vehicle speed allowed by the traffic flow of the city.

The energy consumption equation (2), P_{ij}, is used to compute the road segment's energy cost. It includes two sub-formulas. The first, α_{ij}, is related to the road segment characteristics (3) and the second, β_{ij}, is dedicated to the vehicle speed (4). The vehicle weight μ, the load capacity w_{ij} and the average of the speed on the road network v^t_{ij} are included in the energy consumption equation (2). η is given when the electric car is in motor mode. For our case, the charging capacity is not taken into consideration since we use electric vehicles designed for travel. We outline, first, the used parameters in Table I.

$$P_{ij} = ((\alpha_{ij}(\mu + w_{ij})) + (\beta_{ij}(\sum_{t \in T}(v^t_{ij})^2))) / \eta \qquad (2)$$

Where:

$$\alpha_{ij} = D_{ij}\frac{A + g\sin\alpha_{ij} + g\,C_r}{3600} \qquad (3)$$

$$\beta_{ij} = \frac{0.5 C_d\; a\; p\; D_{ij}}{3600} \qquad (4)$$

4) Charging Station integration

In the case of a battery drop, the driver has to find the possible nearby charging station locations. For this reason, it is important to integrate the charging stations in our algorithm to improve its quality.

This phase matches the charging station positions for the selected region to the segments that they belong to. This process is described by algorithm 1 that uses the Euclidean distance measurements to identify the closest edge for a given charging station.

Algorithm 1 takes as input the list of segment nodes that compose the road network and the list of the charging stations locations in the selected region. The algorithm runs through the road network nodes and computes the distance between the charging station and the current node until it finds the minimum distance. The algorithm, then, affects this charging station to the closest edge.

TABLE I. PARAMETERS OF THE ENERGY CONSUMPTION

Parameters	Symbols	Unit
Road segment characteristics		
The distance traversed from node i to node j	D_{ij}	m
The acceleration value	A	m/s^2
The gravitational constant	g	m/s^2
The rolling resistance coefficient	C_r	-
Vehicle's speed characteristics		
The drag coefficient	C_d	-
The frontal surface area of the electric car	a	m2
The air density	p	Kg/m^3

Algorithm 1 Charging station integration

```
Inputs List of segment nodes, List of charging stations location
Outputs ClosestNode
ClosestNode ← None
Min Distance ← None
if ChargeNode in List of charging station locations then
    for SegmentNode in List of segmentNodes do
        Distance ← Calcul Euclidian Distance(SegmentNode,ChargeNode)
        if MinDistance = None then
            ClosestNode ← SegmentNode
            MinDistance ← Distance
        else
            if Distance < MinDistance then
                ClosestNode ← SegmentNode
                MinDistance ← Distance
            end if
        end if
    end for
end if
return ClosestNode
```

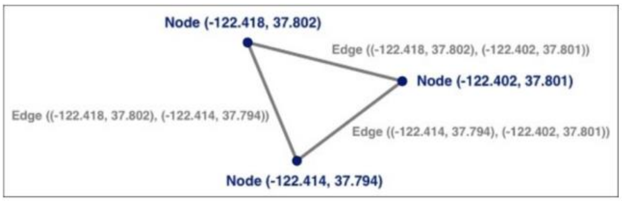


Fig 3. Connections between edges and nodes

5) Constructing the energy graph

The last step of the offline phase is the building of our energy graph based on the previous steps. This energy graph reflects the energy consumption of each road segment during the electric car journey. Based on the road segments, we first model the road network as a graph G = (V, E) with V presenting the set of nodes or intersections between edges on the maps and E denoting the set of edges connecting those nodes. For each edge, we assign a value to reveal the energy consumption as calculated using (2) discussed above. Figure 3 shows the road network construction from nodes and edges.

A path P is a sequence of n nodes $(n_1, n_2...n_m)$ with $(n_i, n_{i+1}) \in E$ for i = (1, 2, . . . , m-1). Other parameters impacting the vehicle's energy consumption are considered including, its mass and air drag coefficient, coefficients of friction, altitude, etc.

B. Second Step: Path finding using A algorithm*

In this step and based on the energy graph, our focus now turns to discover EVs energy consumption amount when passing through an edge in the network. The aim here is to identify the minimum cost of the trip from a given source to a given destination (two vertices belonging to a set of vertices).

Disregarding battery constraints, finding an optimal energy path from source to destination boils down simply to find the shortest path, which is usually solved via the Dijkstra algorithm. However, Dijkstra's drawbacks consist mainly in extending more vertices than necessary [40]. In contrast, the Bellman-Ford algorithm works for graphs with negative weights. This algorithm uses a single source vertex to derive paths to all nodes in the graph, which makes it an inappropriate solution. Moreover, Bellman-Ford is slower than Dijkstra. The A* is faster than Dijkstra's algorithm. It uses the Best-First Search whereas Dijkstra uses Greedy Best-First Search which presents a major disadvantage by the fact that it necessitates a blind search, consuming thereby, a lot of time and a waste of necessary resources. For these reasons, we select the A* algorithm. This algorithm is sustainable for better searching and efficient path-finding in a graph with the lowest cost. It is mostly used when we already know both the source and destination. It's only focusing on reaching the destination node by visiting the minimum number of nodes. This is due to a heuristic, h(x), that gives an estimate of the best route that goes through those nodes. A general description of the A* algorithm is presented in [41].

Before we start using A*, we have to define, first, the two parts of (5). We adapt this graph search algorithm to meet our requirements by developing a heuristic function dedicated to estimate the average energy consumption between two points. A* defines the cost function of an edge f(n) as follows.

$$f(n) = g(n) + h(n) \tag{5}$$

Where, g(n) denotes the cost of moving from the source node to the node n, following the path generated to get there. h(n) presents the heuristic/ approximate energy cost of the path from the node n to the destination.

A* helps to discover the optimal path if the heuristic function h(n) is admissible. That means that h(n) never overestimates the real cost. The heuristic function is based on the Euclidean distance between the two nodes. Then, we calculate the approximated energy consumption using an average energy cost of EVs [42]. Algorithm 2 presents the heuristic function h(n) that returns the approximated kilowatt per kilometer.

A* now is able to find the optimal path given the two nodes and the approximate energy cost. The energy A* functioning is presented by algorithm 3.

Algorithm 2 Heuristic function h: Estimation of the average energy consumption

```
1: Inputs Start Node, End Node, Average Energy Cost
2: Outputs Approximated Energy Cost
3: Distance ← Calcul Euclidean Distance(Node1, Node2)
4: return (Distance / 1000) * Average Energy Cost
```

Algorithm 3 Energy A* algorithm

```
1: Inputs Energy Graph G = (V, E), Start node (s), End node (e),
   Heuristic function h
2: Outputs Optimal path
3: Cost g(s) = 0
4: Cost f = Cost g(s) + Cost h(s, e) (equation 5)
5: Z ← G
6: while Z is not empty do
7:     CurrentNode = Node from Z with Minimum cost f
8:     if CurrentNode = e then
9:         return Path obtained by tracing back the pointers from
10:        CurrentNode to s
11:    end if
12:    Z ← Z/CurrentNode
13: end while
```

C. *Third Step: Trajectory clustering with NEAT*

Traffic prediction is a very powerful technique to better analyze the road conditions based on the clustering of historical trajectory data. The result of this process is a set of clusters that presents the dense routes on the map.

As mentioned before, electric vehicles face a lot of stops while traveling because of the traffic condition. For this purpose, we perform a trajectory data clustering algorithm which allows us to predict the clusters of routes that seem to be blocked. The detection of hot routes is an important problem because each larger city has such hot routes that regularly block the traffic flow at rush hour and thus, traffic participants spend long times waiting in traffic jams.

Several studies were proposed to discover traffic jam in a constrained road network. A traffic detection algorithm that uses the density of traffic in sequences of road segments to discover hot routes in a road network was proposed in [43]. We found also, NETSCAN, a clustering algorithm for road networks [44].

Both studies focus only on the density aspect of the given trajectories. NEAT [45] considers also the flow characteristics and avoids the expensive shortest path computation. NEAT takes into account the physical constraints of the road network, the network proximity, and the traffic flows among consecutive road segments to organize trajectories into spatial clusters.

For those reasons, we select the NEAT trajectory clustering algorithm. The latter is composed of three main phases, including the base cluster formation, the flow cluster formation, and the flow cluster refinements.

To start using the NEAT algorithm, we select the region where the objects are moving. Next, using a trajectory data generator, we create four different trajectory datasets to reflect the possible dense routes in different periods of the day. The output of the NEAT trajectory algorithm is a set of clusters that presents the dense routes in four different periods of the day.

D. *Fourth step: Path selection*

The fourth and final step of our approach is an on-line step where the driver is able now to derive its optimal path. This step takes as input; the start position, the destination, and the battery state of charge. Then, it requests real-time traffic incident information such as accident, congestion, disabled vehicle, planned event, or construction, and the clusters of routes which are predicted to be congested for a given period of the day. Finally, the algorithm selects the optimal path that respects both the battery charge and the location of the charging station when the battery drops. Figure 4 illustrates the different steps of this phase using the notation presented in Table II.

As mentioned before in the off-line phase, our energy graph contains a list of charging stations matched to the edges that they belong to. The algorithm estimates first the real cost of the path computed for a given start and final positions. Then it compares the battery state of charge to the computed path cost.

If the driver is not able to reach his destination with his initial charge, the algorithm finds the possible nearest charging station and derives an optimal path to the destination passing throw this station. If the driver can reach his destination without the need to recharge, an optimal path is just derived.

The algorithm suggests a list of charging stations if they exist on the selected path to remind the driver that he can recharge his vehicle.

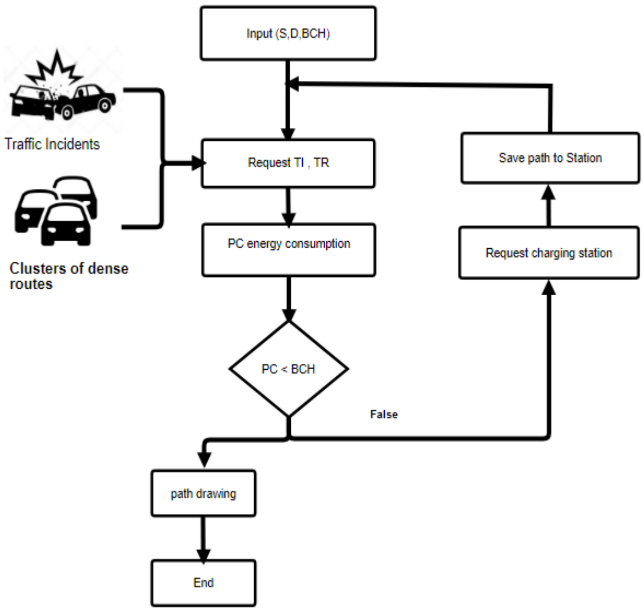


Fig 4. Diagram of optimal path selection process

TABLE II. DIAGRAM NOTATIONS

Notation	Meaning
S	Start position
D	End position
BCH	The battery charge
TI	Traffic incidents information
TR	Trajectories cluster

E. Main Algorithm

In this section, we describe all the steps of our approach within a detailed algorithm (see Algorithm 4).

Algorithm 4 takes as inputs the energy graph constructed during the first phase, the start position, the final destination, the departure time, the clusters of dense routes, the charge of the battery, and the real-time traffic information.

It requests, first, the real-time traffic incidents and selects the cluster of dense routes based on the departure time. Those two parameters deliver the blocked routes that have to be avoided when selecting the path.

The next step consists in map matching the start position and the final destination to the closest two nodes in the energy graph. The A* algorithm, next, delivers the optimal path between the two locations. In case the driver can't reach his destination with the given charge of the battery, the algorithm requests the closest charging station and delivers a new path between the two nodes that pass throw this station.

Algorithm 4 Main Algorithm

Inputs Energy Graph $G(V, E)$, Start Node, End Node, Travel time, Cluster of Dense Routes, Real-time Traffic Incidents, Closest Charging Station, Charge of battery.
Outputs Optimal path
BlockedSegments $\leftarrow$ $RealTimeTrafficIncidents()$
BlockedSegments $\leftarrow$ BlockedSegments + DenseRoutes (DepartureTime)
$G \leftarrow G/$ BlockedSegments
$u, t \leftarrow FindClosestNode(Graph, StartNode, EndNode)$ (Algorithm 1)
Path $\leftarrow$ Energy A* $\times$ (u, t, Heuristic) (Algorithm 3)
Real Cost $\leftarrow$ Cost(Path)
if Charge of battery < Real Cost **then**
  Path $\leftarrow$ $FindClosestChargingStation()$
return Path
end if
return Path

IV. EXPERIMENTAL RESULTS AND DISCUSSION

This section reports the computational results obtained from our framework. Our approach is programmed in java and python and executed on a laptop computer with an Intel Core i5 2.60 GHz processor and 6 GO RAM, operating in the Windows 8.1 environment. The implementation details of our framework and its different composed algorithms are discussed in the next subsections.

A. Parameters description

Our approach considers the two nodes that present the driver's start position and its final destination, the departure time, and the state of charge. To perform the results, our approach requests the real-time traffic incidents and the cluster of dense routes for a given period of the day.

B. Data source and description

To implement our framework, we need to have an appropriate data source of the geospatial data of the road network. Free data are available from different providers which are:

• **Open Street Map:** Open Street Map[1] is a collaborative project to create geospatial map data which is an editable map of the world [46].

• **US Census Bureau:** The US Government produces a large amount of geospatial data provided under the name TIGER[2] (Topologically Integrated Geographic Encoding and Referencing System). The TIGER datasets cover only the United States and provide accurate geospatial data. It includes information about streets, railways, buildings, and geographic boundaries. TIGER data is available in shapefile format [47].

• **Charging Station location:** The information about electric charging station locations is provided in the alternative fuels

[1] https://www.openstreetmap.org
[2] https://www.census.gov/geo/maps-data/data/tiger-line.html

data center (AFDC)[34]. It offers information about alternative fuels resources [48].

- **Google Elevation API:** Google Maps Elevation API[5] provides elevation data from all geographical points on Earth's surface. It also allows us to obtain altitude data to calculate the inclination along a path. All elevation data are expressed in relation to the local mean sea level.
- **Gt-mobisim:** Artificial data simulators use Gt-mobisim simulator[6] for generating mobility traces for a large number of mobile agents moving in a constrained network. These data contain 1000 mobile agents, 2000 raw trajectories and 138107 GPS points.
- **Traffic Incidents API:** To get real-traffic incidents information, we use Traffic incidents data provided by Bing maps Rest services[7]. The Traffic Incident data requested contains information about the selected region, the type of the incident, and its location. The types of traffic incidents are construction, planned events, traffic congestion or accidents.
- **Leaflet Map:** Leaflet[8] is an open JavaScript mapping library widely used by major websites such as FourSQuare. This library allows developers to display points, landmarks, lines and interactive layers such as street markers and popups.

C. Initialization

The initialization phase consists in preparing the energy graph that is used, next, to derive the optimal path. It regroups steps such as the route partition, the road energy computation and the graph construction.

1) Road processing and segmentation

First, we select a region from the geospatial map to work with. The energy graph is based on the road network of the selected region. The providers of these maps deliver a shapefile which is a geospatial vector data that describes features such as points, lines and polygons that represent buildings, roads, lakes and rivers, etc. Since we are interested in route planning, we select only the roads layer which is a collection of lines.

To ensure the quality of the road network, we filter the list of the roads needed to construct the graph from all roads such as stairway, airport, private park, private roads, bike path and foot-way.

Among the different fields presented in the shapefile, the MAF/TIGER Feature Class Code (MTFCC) field is needed to select the road class codes that we need when constructing the graph. The list of road class codes is presented in table III. The Postgres database is updated with these roads while preserving their geometries. PostGIS ensures loading roads into databases when encoding their features.

The next step is dedicated to the route partition process. For this, we use a standard road partition algorithm presented in [37], where we generate a list of road segments that construct, next, our graph.

2) Road energy computation

We calculate the road segments elevation using (1) presented in section 4. We use the Google Elevation API that provides elevations for each point on the earth. Based on vehicle parameters and (2) presented in section 4, we calculate the energy cost of each road segment using the vehicle parameters values shown in table IV as provided in [23].

3) The trajectory clustering with NEAT

We implement the NEAT algorithm with the datasets generated by Gt-mobisim. NEAT establishes an efficient trajectory clustering of the data and generates a cluster of dense routes for different periods of the day, as shown in table V. The graph is constructed at the query time where we request the Bing Rest API to identify roads with unexpected incidents. We restrict the roads resulted from the Bing traffic API.

We use data from the city of San Jose' in California, US. The energy graph of this state contains 7679 nodes and 10887 edges.

Figure 5 illustrates a set of clusters of the dense routes generated using the NEAT algorithm in the city of San Jose.

TABLE III. ROAD CLASS CODE

Road Code	Description
S1100	Primary roads
S1200	Secondary roads
S1740	Residential roads
S1400	Trunk roads

TABLE IV. VEHICLE PARAMETERS VALUES

Parameters	Values
C_r	0.01
A	55
a	8.0
G	9.81
Cd	0.8
p	1.225
η	0.76

TABLE V. NUMBER OF CLUSTERS PER TRAVEL TIME

Travel Time	Number of Clusters
7:00 - 9:00	16 Clusters
9:00 - 17:00	11 Clusters
17:00 - 19:00	14 Clusters
19:00 - 7:00	10 Clusters

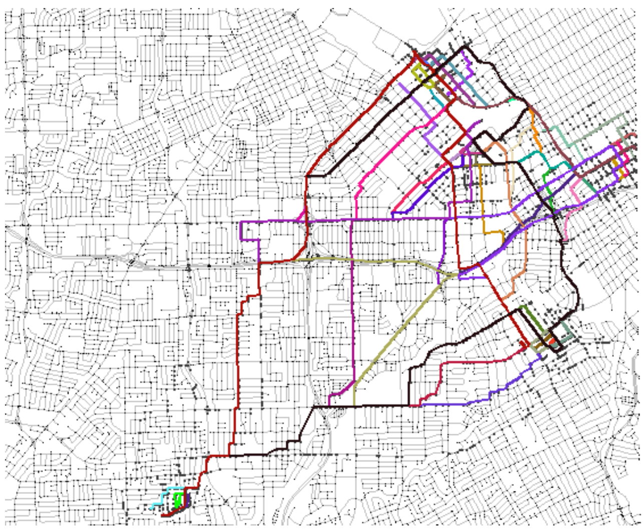


Fig 5. Clusters generated by NEAT in San Jose

[3] https://www.openstreetmap.org
[4] https://www.afdc.energy.gov/fuels/electricity_locations.html
[5] https://developers.google.com/maps/documentation/elevation/intro?hl=fr
[6] https://code.google.com/archive/p/gt-mobisim/
[7] https://msdn.microsoft.com/en-us/library/hh441726.aspx
[8] http://leafletjs.com/

D. Experiments and Results

In this section, we present the experimental results. First, we describe different scenarios. Then, we analyze the parameters affecting path efficiency. We compare also the results of each parameter to the efficiency of all parameters combined. Finally, we compare their solution with other solutions.

1) Results

To evaluate the effectiveness of our algorithm, we visualize the discovered paths with different queries. The first query presents the derived optimal path given the two nodes and the battery state of charge. In case the battery is charged, the driver can reach the destination without the need to recharge along the way. Figure 6 (a) presents the optimal path with the existing charging station on it.

The second query is similar to the first one but with a low battery charge. In this case, the algorithm derives the path with a red sign to inform the driver where he should recharge his electric car. This path is presented in figure 6 (b).

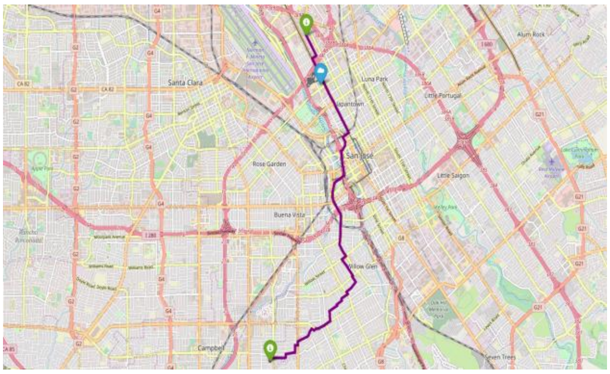
The last query presents the alternative optimal path with a low battery charge, where, there is no charging station. In this case, the algorithm requests the nearest charging station reachable by the driver. Figure 6 (c) illustrates the alternative optimal route from the current location to the destination passing throw the charging station.

2) The approach evaluation

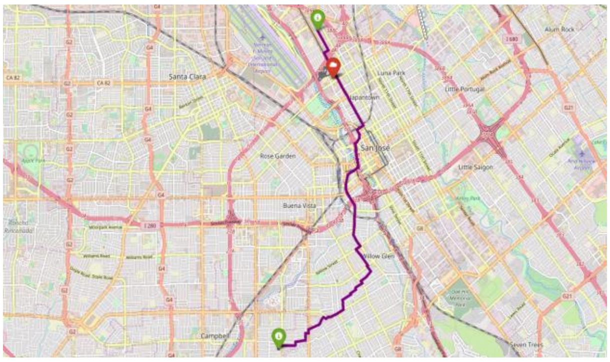
In this section, we study the effect of varying the parameters used in our approach to evaluate its performance against different scenarios.

• Impact of the distance

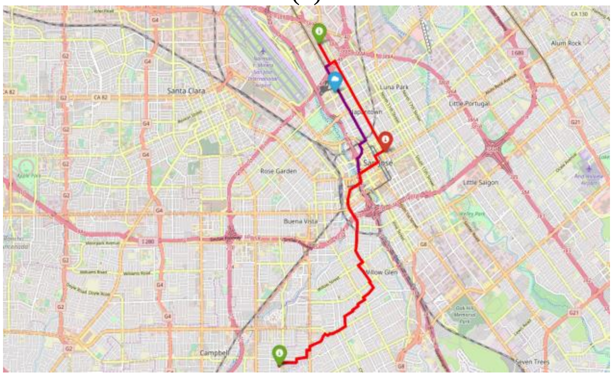
We evaluate the derived path with the shortest path to study the distance impact in discovering the optimal path. Using the same parameters, we found that the shortest path (red line) is shorter in terms of distance but its energy consumption is greater than the optimal path. The shortest path costs 4.3 kWh for 3 km against the optimal path (purple line) that costs only 2.2 kWh for 4.2 Km. This is due to elevations and congested routes contained in the shortest path. Figure 7 illustrates the two different routes.



(a)



(b)



(c)

Fig 6. Discovered paths with different queries (a) Optimal path with charging station (b) Optimal path with the need to charge (c) Alternative Optimal path with charging station

• Impact of the elevation

We study the elevation impact on the delivered path. We evaluate the first path using only the vehicle parameters against the path considering the inclination values. As shown in figure 8, the red line presents the path using only the vehicle parameters without considering the elevation factor. It costs 4.12 kWh against the optimal path (purple line) that considers the elevation factor and costs 2.2 kWh. The elevation of each path is shown in figure 9. Figure 9 (a) presents a soft inclination which ensures the efficiency of the path and reduces energy consumption. Figure 9 (b) presents a heavy hill where the path derived does not consider the elevation.

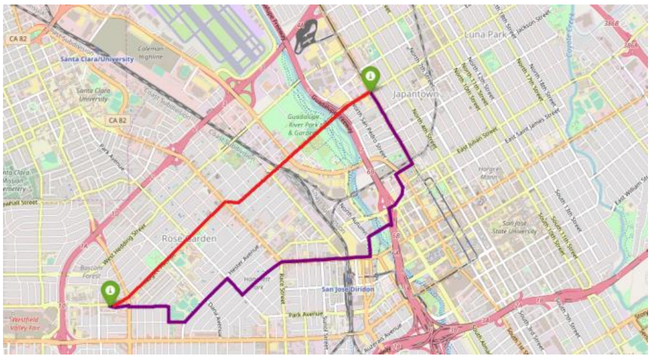


Fig 7. Optimal path Vs shortest path

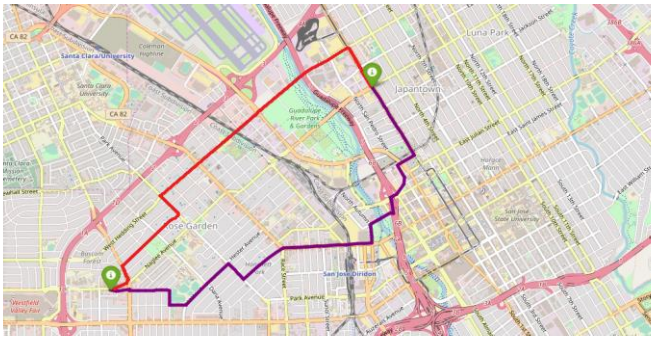


Fig 8. Paths with elevation (purple line) Vs path with vehicle parameters (red line)

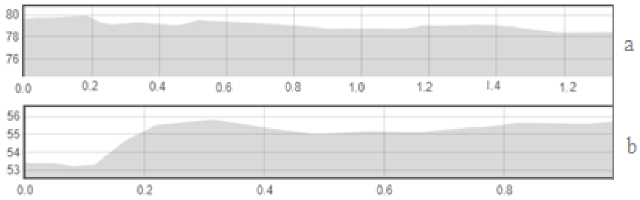


Fig 9. Elevation Difference between the two paths (a) Path with a heavy hill (b) Path with a soft inclination

• Impact of the API Incident

We study the importance of real traffic incidents using Bing maps Rest services that provide blocked routes list in the road network, given the boundary box of the selected region. Two paths are presented in figure 10 (a) and 10 (b), the first is based on real traffic incidents that avoid getting stuck on a blocked route. The algorithm derives an optimal path that prevents the blocked routes which is not the case in figure 10 (b) that passes throw the blocked route and may reduce the efficiency of the path.

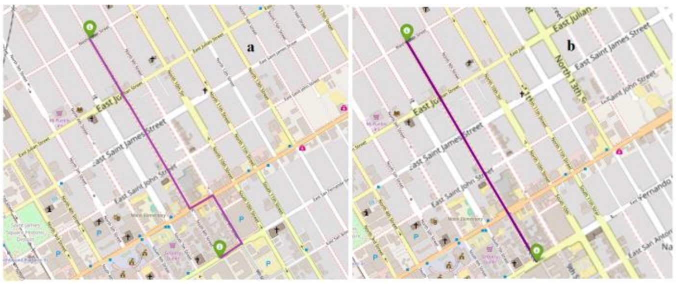


Fig 10. Optimal Paths using Real traffic incidents (a) Path that avoids the blocked route (b) Path that passes throw the blocked route

• Impact of the cluster

We study the traffic flow prediction effect by considering the clusters of dense routes obtained using the NEAT algorithm. Figures 11 (a) and 11 (c) show the derived paths on the two periods of rush hours. Figure 11 (a) presents the optimal path during the first rush hour (7h00 - 9h00) with an energy cost of 3.2 kWh. Figure 11 (b) presents the optimal path during the next period (9h00 - 17h00) with an energy cost of 2.7 kWh. The next optimal path is derived in the second rush hour (17h00 - 19h00) with an energy cost of 3.3 kWh (Figure 11 (c)). Figure 11 (d) presents the optimal path during the period (19h00 - 7h00) with an energy cost of 2.5 kWh.

Fig 11. Optimal paths for different periods of the day (a) Optimal path during the first rush hour: 7h:00-9h:00 (b) Optimal path during the next period: 9h:00-17h:00 (c) Optimal path during the second rush hour: 17h:00-19h:00 (d) Optimal path during the next period: 19h:00-7h:00

• Impact of the charging station

We describe, here, the impact of the integration of the charging stations on the map. First, we derive an optimal path that passes throw the charging station as presented in figure 12. The red icon presents where the driver should charge his electric car. From all charging stations on the map, we select the one that the driver can reach when using the optimal path.

Figure 13 presents the derived path that passes throw one closet charging station when the battery state of charge does not allow the driver to reach the destination. The red line shows the deviation of the path needed to pass throw the charging station.

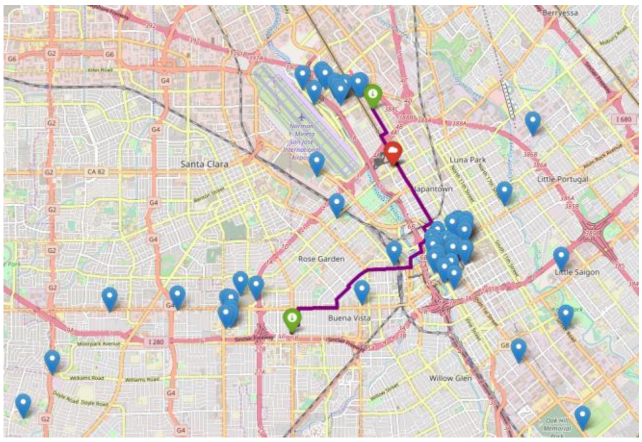


Fig 12. Optimal paths with charging station

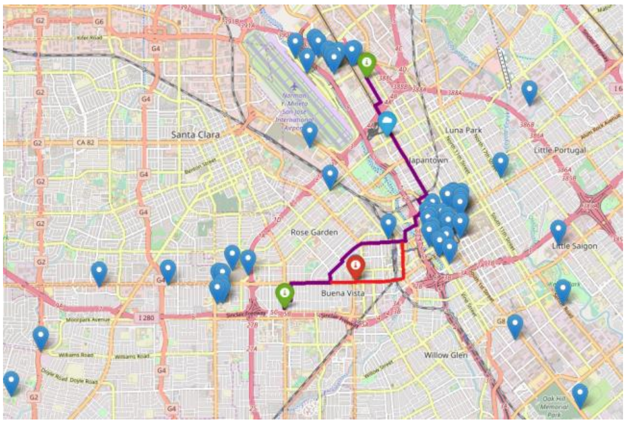


Fig 13. Alternative optimal path with charging station

• Results comparison

We compare the efficiency of the optimal path for a given parameter against all parameters combined. Table VI presents the different path costs for the same source and destination. The comparison result shows that the shortest path and the paths based on both traffic prediction and traffic incidents have higher energy consumption. This is because they ignore the road topology characteristics. The route that considers road topology has the lowest cost. However, this path may pass throw blocked routes or traffic jams which can reduce road efficiency and increase the path cost. Comparing the optimal path for a given parameter against considering all parameters together, we can conclude that the latter has the suitable path energy consumption. This is because it is more realistic and the path derived avoids getting stuck in blocked in the predicted dense routes.

TABLE VI. PARAMETER RESULTS COMPARISON

Used Parameters	**Energy optimal path cost**
Distance (shortest path)	3.1 kWh
Elevation	1.8 kWh
Traffic incidents	2.9 kWh
Traffic incidents + Elevation	1.9 kWh
Traffic Prediction	3.5 kWh
Traffic Prediction + Elevation	2.7 kWh
Traffic Prediction + Traffic incidents	3.7 kWh
All parameters	**2.8 kWh**

3) Discussion

After evaluating the effectiveness of our EVs route planning algorithm on several scenarios, we are interested comparing the new algorithm with other studies in the literature. We choose to compare our method to the study of [49], an approach to energy-efficient routing of electric vehicles. In this study, the authors focus on applying the Bellman-Ford algorithm on different map sizes. They generate a solution from a single source vertex to all nodes in the graph with the presence of negative edges. Table VII shows the comparison results.

Comparing our algorithm to the Bellman-Ford algorithm, we found that once the number of vertices and edges becomes high, the Bellman-Ford becomes impractical and cannot be used to solve the problem of route planning for electric cars. Our algorithm however can deliver real-time results with reasonable running time. It also considers real-time traffic incidents and the prediction of the dense routes for given travel times. This can avoid getting stuck in those blocked road segments, which is not provided in the Bellman Ford approach. Furthermore, our algorithm considers the location of charging stations and the battery state of charge which was missed in [49] approach.

We compare also our algorithm to another study provided by Nunzio et al. [50] for the prediction of the optimal driving range for EV. As presented in Table VIII, we compare our algorithm against another Bellman-Ford approach in the city of Bologna.

The results show that our algorithm runs faster than the Bellman Ford algorithm. In this study, the authors try to predict the driving range of EVs from a single source to the reachable nodes in the graph. But, they fail to integrate the real-time traffic incidents which reduce the accuracy of the predicted driving range. They didn't also specify the optimal paths that save energy. Nunzio et al. [50] consider the regeneration mode to recuperate energy downhill contrary to our algorithm that takes into account the charging station locations.

TABLE VII. TIME TO GENERATE SOLUTION

Number of Vertices	**Number of Edges**	**Time to generate Solution**	
		Bellman-Ford	**Our solution**
20	37	0.054 sec	0.15 ms
29	63	0.138 sec	22 ms
294	1.152	25.80 sec	124 ms
988	10.026	774.8 sec	0.3 sec
16.340	270.780	203 hours	-

TABLE VIII. RUNNING TIME COMPARISON OF THE TWO ALGORITHMS

Bologna Map			
Number of Vertices	**Number of Edges**	**Time to generate Solution (sec)**	
		Bellman-Ford	**A* algorithm**
6,111	11,543	2.24	0.4

V. CONCLUSION AND PERSPECTIVES

In this paper, we consider the route planning for electric cars. The purpose is to discover efficient optimal routes for EVs based on multiple travel costs. We develop a new route planning algorithm for electric cars that takes into account real-time traffic incidents, the traffic flow, the road topology, and the location of charging stations. Tests were made on the city of San José in California, US. Our approach was also compared with other approaches, and yielded very good results.

As future works, we can improve the quality of the segmentation process to better detect curves on-road segments instead of using the standard segmentation process. Moreover, we are interested in using real traffic information and real trajectory datasets to reach optimal accuracy. We can also improve the exactitude of the path by relying on available charging stations and vehicle particularities in real-time. Besides these three perspectives, a deep statistical analysis will be considered in future extensions of this work.

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