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PAPER

AFARM: Anxiety-Free Autonomous Routing Model for Electric Vehicles with Dynamic Route Preferences

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ABSTRACT

Energy and environmental concerns have fostered the era of electric vehicles (EVs) to take over and be welcomed more than ever. Fuel-powered vehicles are still predominant; however, this trend appears to be changing sooner than we might expect. Countries in Europe, Asia, and many states in America have already made the decision to transition to a fully EV industry in the next few years. This looks promising; however, drivers still have concerns about the battery mileage of such vehicles and the anxiety that such driving experiences! Indeed, driving with the probability of having insufficient battery charge that may be involved in guaranteeing the delivery to the trip destination imposes a level of anxiety on the vehicle drivers. Therefore, for an alternative to traditional fuel-powered vehicles to be convincing, there needs to be sufficient coverage of charging stations to serve cities in the same way that fuel stations serve traditional vehicles. The current navigation models select routes based solely on distance and traffic metrics, without taking into account the coverage of fuel service stations that these routes may offer. This assumption is made under the belief that all routes are adequately covered. This might be true for fuel-powered vehicles, but not for EVs. Hence, in this work, we are presenting AFARM, a routing model that enables a smart navigation system specifically designed for EVs. This model routes the EVs via paths that are lined with charging stations that align with the EV's current charge requirements. Different from the other models proposed in the literature, AFARM is autonomous in the sense that it determines navigation paths for each vehicle based on its make, model, and current battery status. Moreover, it employs Dijkstra's algorithm to accommodate varying least-cost navigation preferences, ranging from shortest-distance routes to routes with the shortest trip time and routes with maximum residual battery capacities as well. According to the EV driver's preference, AFARM checks the set of candidate paths at the source point and selects the appropriate path for the vehicle to drive based on its current status. Consequently, AFARM provides an anxiety-free navigation model that allows for a reliable and environmentally friendly driving experience, promoting this alternative mode of transportation.

KEYWORDS

EVs routing model, anxiety-free routes, tactical autonomous routing

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1 INTRODUCTION AND PROBLEM STATEMENT

Recently, the theme of electric vehicles (EVs) has emerged as a promising alternative to traditional fuel-powered vehicles. EVs are not only powerful but also friendly to the environment and the economy. Indeed, with no fossil sources to burn, EVs emit no carbon dioxide or any other pollutants or greenhouse gases. For drivers, the use of EVs is considered cost-efficient, as it involves not only the costs of energy but also maintenance. True, EVs are constructed with simpler mechanical designs that provide higher torque power, eliminating the need for gearbox conversions or oil-consuming components. On the other hand, this transportation technology may also bring about a sense of anxiety, particularly for individuals driving long distances!

1.1 Problem

Driving with the probability of having insufficient battery charge that guarantees the delivery to the trip's destination imposes a level of anxiety on EV drivers [1], [2]. Navigation systems for fuel-powered vehicles are excellent, as they accurately determine the optimal routes based on metrics that ensure the shortest or fastest trips to the desired destinations. To some extent, this could work for EVs as well. However, a route that suits a fuel-powered vehicle may not necessarily suit an EV. Certainly, the routes chosen by traditional navigators are assumed to have fuel stations to serve vehicles traveling along them. However, for EVs, the question arises: are these routes also equipped with electric charging stations to cater to the needs of EVs? If so, would this coverage suit all those EVs that come with varying battery capacities? The subsections that follow will elaborate on the challenges.

EVs varying makes and models. Electric vehicles vary in their battery sizes and energy consumption, leading to varying requirements. An EV with a large battery capacity may take routes that are not suitable for vehicles with limited or relatively small battery capacities. Therefore, an efficient route selection process needs to consider the EV make and model in addition to the other inputs of source and destination points.

Battery state of health. Moreover, even for those EVs that are from the same make and model, batteries also vary in their state of health (SoH). SoH is an important factor that refers to the aging state of the battery cells, which greatly affects the expected battery performance. Accordingly, EVs vary in their charging requirements even if they are from the same make and model, which means their route requirements would also vary. As an example, in the EVs automobile sector, various makes and models of EVs exist, each with different specifications and varying battery ranges. This ranges from 120 km for a fully charged battery to 600 km or even more. For a trip of 500 km, a fully charged EV, with a range of 600 km, would reach the trip's destination without needing to be charged. In contrast, a 240 km range EV would need to be charged twice, and a 120 km range EV would need to be charged at least four times.

Driving conditions. Factors such as driving mode, time of day, and weather conditions may also affect the actual range of the battery. Indeed, driving in sport mode consumes a different amount of energy compared to classic or eco modes, even for the same EV make and model. The same applies when considering driving during the day or at night, in sunny or cold weather conditions. Each has its own specific requirements, such as lighting, air conditioning, heaters, wipers, and so on. This may also extend to road conditions, including challenges such as mud and snow.

Therefore, the process of route selection for electrically powered vehicles is more complex compared to traditional fuel-powered vehicles [3]. The adequate coverage of suitable charging stations for electric vehicles is crucial in such situations. Truly, a route that may suit an EV may not suit another, even if they are from the same make and model.

With the adoption of the new theme of the eco-friendly transportation industry by governments and countries worldwide, cities need to address the aforementioned coverage problem by ensuring appropriate coverage along all routes, both interior and exterior. This looks promising; however, it may take a while to materialize! Accordingly, in this work, we are presenting AFARM, a model built to assist in routing EVs based on existing road-network maps [4], but adapted to find routes that meet the varying requirements of EVs. In this context, the proposed navigation system needs to be "autonomous and dynamic" for two main reasons: (1) it should track the specific make and model of the running EV to determine the most suitable navigation routes, and (2) the selected routes should be continuously updated in real-time to adapt to any changes in the EV or road network conditions. Taking that into account, the model is developed to offer the following route navigation options: (1) the shortest distance routes; (2) the routes with the maximum residual battery capacities; and (3) the fastest routes in terms of time.

1.2 Contribution

Finding the shortest matching paths is a significant advancement. However, for an efficient navigation system for EVs, there are additional concerns that need to be addressed. In most cases, the anxiety mentioned above does not dissipate upon reaching the destination of the trip; rather, drivers may require their EVs to retain ample residual battery charge before embarking on a new trip. Such charges are sufficient to guide them to the nearest charging station along their routes to their new destinations. What is more, finding the shortest path that is guaranteed to have the appropriate charging stations is great. However, for some drivers, the total time of the trips is also an important factor to consider. A path that is defined as being the shortest (in terms of distance) is not necessarily the fastest! Indeed, the shortest path that passes through more charging stations may require a longer trip time compared to another path with longer distances but fewer charging stations. True, the time spent charging at the charging stations along the route is included in the total trip time calculation, in addition to the propagation times. Therefore, stopping at more charging stations will inevitably result in longer trip times. In this work, in addition to the goal of shortest path routing, we are extending our focus to address the concerns of residual battery capacity and total trip times. Briefly, this work contributes by presenting a navigation model that is:

- Anxiety-free, as it navigates the routes of trips from their starting points to their destination. These selected routes are guaranteed to have the necessary charging points, if needed. So, the anxiety of being on the side of the road is eliminated.
- The tactical approach involves selecting routes for running trips that ensure there is enough battery charge capacity to initiate new trips. A form of strategic planning involves being ready for upcoming journeys.

- The shortest navigation model identifies all possible paths for the vehicle starting at the source point. Among the candidate paths, the system selects the shortest suitable route for the EV in operation.
- Fastest: Time wise, this route differs from the shortest distance routes as it considers the trip's distance in kms and the number of charging points to pass through.
- Autonomous: each EV is treated as an independent entity utilizing its navigation system. Therefore, even if multiple vehicles have the same source-destination points, they may receive different routing decisions.
- The model is dynamic, continuously monitoring the vehicle and road conditions in real-time, and adjusting the selected paths as needed.

The rest of this paper is organized as follows: Section 2 presents some related work, and Section 3 discusses our proposed routing model, followed by the methodology in Subsection 3.1. Section 4 presents the benchmark model, and Section 5 showcases and discusses a sample of the simulation results that were conducted to assess and compare the model. Finally, Section 6 concludes the paper.

2 RELATED WORK

Several proposals in the literature have addressed the area of EVs and their related research problems. Mostly, they address issues to safety, power consumption, battery manufacturing technologies, and cybersecurity risks [5]. When it comes to charging, most of the research focuses on power grids, load-balancing, wired/wireless charging techniques [6], and scheduling from both economic and load perspectives [7], [8], [9].

For the problem of routing and path selection for EVs, in [10], the authors proposed a routing model that claims to solve the issue of range anxiety. They proposed creating a polygon-shaped area as a navigation space towards the vehicle's trip destination. For the polygon area, the model defines four reference points starting with the charging request point. Their proposal may include a route that could be lined with charging stations leading to the destination. While, such a path selection model lacks guarantees that it will meet the "running" EV charge requirements or choose the true shortest path to the destination. Indeed, a path that may suit an EV may not suit another from a different make or model. Moreover, without considering the running EV battery charge and SoH, those selected paths might be misleading. True, this could occur in two cases: (1) If the chosen route does not have an adequate number of charging stations, the EV may run out of battery along the way and require towing. (2) If the selected route includes unnecessary charging stations, a shorter path could exist if these extra stations were not mandatory on the navigation route.

In the same domain of research, the work of [11] proposed an autonomous adaptive routing model that aims to enhance the path selection process outlined in [10], and introduces a cognitive model that takes into account the type of EV in the routing process. The proposal in [11] is also adaptive, as it adjusts the path selection process to any changes or updates that occur in the vehicle's or road's status in real-time. Compared to the navigation paths chosen in [10] the model presented in [11] is cognitive, adaptive, and shorter. However, restricting the search domain for a charging station to a relatively small area, as suggested in [11], may not guarantee the selected navigation paths are the shortest. Indeed, such zone limitations may allow for a relatively short path, but not necessarily the true shortest. In [12], the authors proposed a novel routing methodology that encompasses all the relevant paths between pairs of source and destination points for trips. In this context, the term “appropriate” refers to paths that align with the EV’s profile and the coordinates of the trip. In the same context, the work presented in [14] discusses a time-window-constrained route navigation model that assumes a fixed cargo weight and static power consumption rates. Furthermore, their work assumes static traffic loads on the vehicle routes, which are more dynamic than static in real-life settings. Indeed, such assumptions are hard to meet, as vehicles carry a varying number of passengers and cargo weights, and therefore, their energy consumption rates would also vary. In our AFARM model, the route selection process involves reading the dynamic EV status and then identifying suitable candidate routes.

In [15], the authors proposed an EV navigation model that aims to find shorter route distances compared to those of fuel-powered vehicles. In our model, finding a short route is a priority. However, battery-wise, such short routes need to guarantee the delivery of the trips’ destination points. Our AFARM model is autonomous as it searches for the shortest-matching routes that ensure the running EV’s battery matches the driving status requirements.

The proposal in [16] addressed the same issues, but from a different perspective. Minimizing the total trip time was the focus of the study [16]. While it is a crucial priority, achieving minimal travel times may result in longer distances, which can be challenging for EV drivers with limited battery ranges. From the perspectives of infrastructure, market, and drivers’ feedback and preferences, such new alternatives to the existing transportation systems have been discussed in [13].

The work in [17] includes proposals related to the management models of energy supply to the main power grids under study. In references [18], [19], and [20], the authors addressed the challenges of dynamic billing to regulate electricity power consumption rates. In the same context, the work in [21], [22], and [23] addressed billing mechanisms that could be deployed to incentivize EV charging activities during specific periods of the day. Using an appropriate notification mechanism [24], this would be truly useful when considering the EVs potential loads on the electricity power grids, but not for navigation and EV routing services.

Compared to the other models in the literature, our proposed model, AFARM, is autonomous. It determines navigation paths for each vehicle based on its make, model, and current battery status. Moreover, it allows for various navigation preferences, ranging from shortest-distance routes to routes with maximum residual battery capacity, as well as shortest trip-time routes. According to the driver’s preference, it checks the set of candidate paths at the starting point and selects the most suitable path for the vehicle to drive on.

3 THE PROPOSED ANXIETY-FREE AUTONOMOUS ROUTING MODEL

This section presents our routing model for EVs, which offers an autonomous and dynamic route solution with various preferences. A navigation model, as illustrated in Figure 1, considers the EV profile, battery state of health, trip’s origin and destination points, driver’s route preference, and autonomously determines the optimal route that best fits the EV and its driver. In such a scenario, we assume there are 25 different charging stations providing coverage over a specific geographical area. We also assume that there are three varying EVs traveling in this area, each with a unique profile, battery SoH, trip coordinates, and driver preferences.

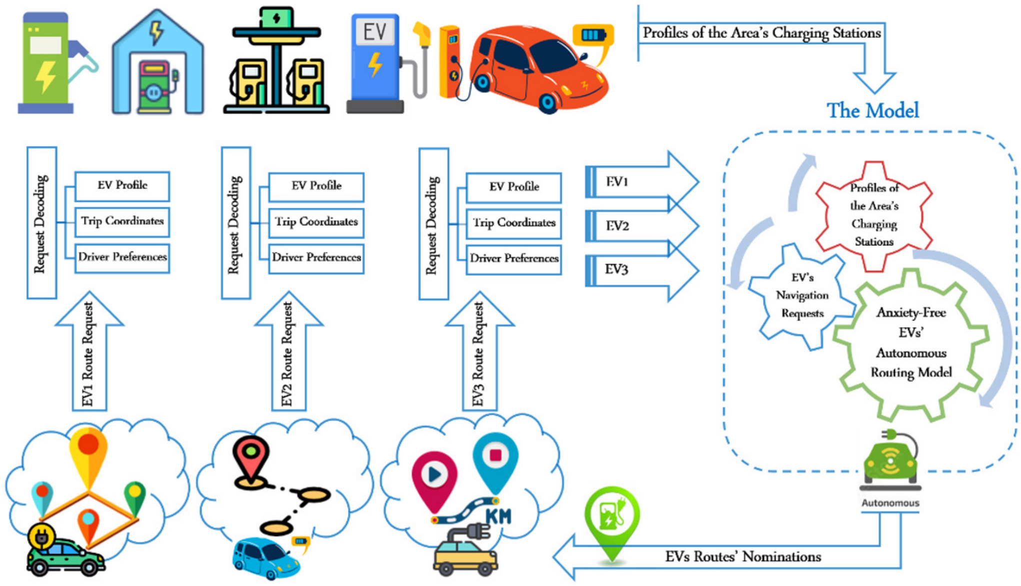

Fig. 1. A Demonstration to the proposed EVs' autonomous routing model

3.1 Model's methodology

Different from the benchmark model [10], which considers the charging request point as the initial reference for the search area, our proposal involves finding the routing path $\mathfrak{R}_{ev_i}$ with respect to the trip's starting point. Moreover, our model reads the following information (1) EV make m, m ∊ M, (2) the EV model e, e ∊ E, (3) its battery charge β_{ev_i} in kWh, SoH, and (4) the EV's power consumption profile ρ_{ev_i} in kW/kWh, along with (5) the source s_{ev_i} and destination d_{ev_i} points of the desired trip. As presented in Equation (1), the model calculates the vehicle's battery range limit in kilometers or miles. Consequently, it determines the longest distance $\uparrow D_{ev_i}$ the vehicle can travel before needing to be charged. This could be bounded by the value α, which helps define a desired usable limit for the total battery capacity.

$$\uparrow D_{ev_i}(\mathrm{m.e}) = \alpha\left[\beta_{ev_i} * \rho_{ev_i}\right] \tag{1}$$

Having such value of $\uparrow D_{ev_i}$, and different from the work in [11], as shown in Equation (2) below, the model finds a set of candidate charging points c_i, $c_i \in C$, that are reachable within a distance D_{c_i} less than or equal to what is $\uparrow D_{ev_i}$ calculated in Equation (1) from the trip's source point s_{ev_i}, or a desired threshold value.

$$D_{c_i} \le \uparrow D_{ev_i}.\ \forall\ c_i \in C \tag{2}$$

However, beside the distance condition of Equation (2), for each running, this list is bounded with the following set of constraints:

Model's constraints.

- **Compatible charging points:** Among those charging points c_i, $c_i \in C$, that satisfy the distance condition of Equation (2), only the charging points compatible with the make and model requirements of the vehicle are considered potential charging candidates; others are exempted. As shown in Equation (3), the model identifies the compatible points in C_{ev_i}.

$$C_{ev_i} = \begin{cases} 1 & \text{if point } c_i \text{ is compatible with } ev_i : m.e \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

- **Charging points' reachability:** The selected points in Equation (3) need to satisfy an additional filtering constraint, the reachability constraint. This constraint necessitates that each point in RC_{ev_i} to allow for a path to reach the trip's destination point d_{ev_i}, either directly or indirectly, as illustrated in Equation (4). Therefore, the model excludes any charging point that does not contribute to the journeys' destination. So, any charging points whose neighboring charging points are further away than the EV's distance limit is excluded from the list.

$$RC_{ev_i} = \begin{cases} 1 & \text{if point } c_i \text{ allows for a path to } d_{ev_i} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

3.2 Routing with trip distance perspective

After obtaining the list of candidate charging points that meet the model constraints in RC_{ev_i}, it calculates the distances for the paths $vP_z^l . z \in Z$, each candidate charging point, $c_i \in RC_{ev_i}$, can take to reach the trip's destination point d_{ev_i}. In real-time, this information is added to the list RC_{ev_i}.

If the selected navigation mode is the shortest trip distance, the candidate paths are sorted based on their distances in descending order. The path with the shortest distance, vP_z, is then chosen as the navigation route to follow. The selected route not only provides directions and other road attributes but also highlights the charging points where the EV needs to stop and recharge its battery if necessary.

3.3 Routing with residual battery capacity perspective

Different from the benchmark model [10], which considers the charging request point as the first reference for the search area, our proposal determines the routing path $\mathfrak{R}_{ev_i}$ with respect to the trip's origin point. Moreover, our model reads the following information: (1) EV make m, m $\in$ M, (2) the EV model e, e $\in$ E, (3) its battery charge β_{ev_i} as in kwh, with its SoH, (4) the EV's power consumption profile ρ_{ev_i} in kW/kWh, and (5) the source s_{ev_i} and destination d_{ev_i} points of the desired trip. As presented in Equation (1), the model calculates the vehicle's battery range limit in kilometers or miles. This value represents the longest distance $\uparrow D_{ev_i}$ the vehicle can travel before needing to be recharged. This could be done with the value α, which helps define a desired usable limit for the entire battery capacity. In addition to distance routing, the option of considering residual battery capacity can be incorporated into the route selection methodology. After returning home, maintaining residual battery capacity is one of the primary goals that EV drivers consistently strive to achieve after each trip. This ensures they can embark on their next journey without any worries about power availability.

To meet this requirement, our proposed routing model allows the selection of paths that offer the maximum possible residual battery capacities. To do this, the model must identify the final charging point that the EV used just before reaching its destination. To facilitate this, we proposed the following definitions to classify candidate charging points, $c_i \in RC_{ev_i}$, to either direct or indirect ones:

- **Definition 1:** Direct path charging points are that undergo pass a distance verification step to determine if the trip's destination point d_{ev_i} is within the distance limit $\uparrow D_{ev_i}$ that the vehicle ev_i can reach from the starting point c_i, $c_i \in RC_{ev_i}$, with a fully charged battery. Accordingly, the list RC_{ev_i} is updated $R^d_{C_{ev_i}}$ as shown in Equation (5) to filter the candidate charging points based on their reachability options, which can be either direct or indirect.

$$R^d_{C_{ev_i}} = \begin{cases} 1 & \textit{if point } c_i \in RC_{ev_i} \textit{ allows a direct path to } d_{ev_i} \\ 0 & \textit{otherwise} \end{cases} \tag{5}$$

- **Definition 2:** Indirect charging points are those that provide a route to the trip's destination point d_{ev_i}, but through other charging points along the way. This means that the point d_{ev_i} is located beyond the reachability limits of the examined point c_i. Such points are treated as new source points for the trip. Consequently, the model determines the next charging points (i.e., relay points) that must adhere to the constraints outlined in Equations (3), (4), and (5) once more.

  Hence, for those points that satisfy the aforementioned definition of direct charging points, the model calculates the distances between these points and a chosen trip destination point d_{ev_i}. With the distances being found, the model estimates the expected residual battery capacity β_{ev_i} at the destination point for each point d_{ev_i}. Having said that, the model sorts the paths accordingly and then chooses the path that provides the maximum residual capacity to drive through.

3.4 Routing with trip time perspective

In the same way that Internet routing protocols use metrics to prioritize one path over another, these metrics may vary from on network to another or from one autonomous system to another. Our navigation model also accommodates different route metrics for selection. In this context, in addition to the options of the shortest distance and the maximum residual capacities, the option of trip time is also available. This includes the travel time (i.e., the propagation time) and, if necessary, the charging time (i.e., the time the EV takes to charge at the selected charging stations along the route).

It is worth highlighting that this may also include the waiting times at the charging stations, which vary from one station to another. However, in this work, we assumed no queues at the charging stations to wait for being served, and so the waiting time is not considered. Accordingly, those paths with more charging stations to pass through might not be preferred for drivers who have time concerns. Therefore, the model can find them other paths that may come with longer distances to drive but less total trip time as they pass through fewer charging points.

$$\nu P^t_z\ (ev_i) = ₣\left(D_{\nu p_z}\right) + \gamma(\aleph) \tag{6}$$

To do so, for each candidate path to drive, the model finds the number of relay nodes $\aleph$ (i.e., the charging points or route hops) and accordingly adds the charging time to the drive time as shown in Equation (6), where ₣ is a time unit set per one kilometer distance, $D_{\nu p_z}$ is the distance, calculated by the model for the assigned path ν_{p_z}.
The parameter γ is a service time unit assigned to each instance the EV stops to charge at a charging station along the entire route, and consequently, it is multiplied by the number of stops $\aleph$ (i.e., the path hops) along the path. Once calculated, the

model adds these time values νP_z^t to the list RC_{ev_i}. Once sorted accordingly, the system can select the path with the shortest travel time.

3.5 The model's routing algorithm

Table 1 presents the proposed anxiety-free autonomous routing algorithm for EVs with dynamic route preferences. The algorithm summarizes the aforementioned discussion, and as is clearly noticed, the model runs autonomously based on the EV's current status and the attributes of the trip's points. Hence, once the EV reaches the chosen charging point c_i, we run the navigation process all over again starting from the point c_i as a new source point. Therefore, according to the new charge status, the model chooses the next part of the route towards the trip's destination point d_{ev_i}.

Table 1. Anxiety-free autonomous routing algorithm for EVs with dynamic route preferences

The Model's Routing Algorithm
1: *input: Read the* ev_i *make* $m, m \in M$, and model $e, e \in E$, then:
2: read the trip's source and destination points s_{ev_i}, d_{ev_i},
3: read the vehicle's battery State of Health SoH,
4: read the vehicle's battery charge status β_{ev_i},
5: read the vehicle's power consumption profile ρ_{ev_i},
6: **for** the given EV's make and model (m, e), and the distance threshold $\uparrow D_{ev_i}$;
7: **run** the model, and list the candidate charging points c_i in C_{ev_i},
8: **while** the list C_{ev_i} is not empty, **examine:**
9: the compatibility of each point c_i, and update the list C_{ev_i},
10: the reachability of each point c_i to the destination point d_{ev_i},
11: **update** the list C_{ev_i} in RC_{ev_i},
12: **for** the list RC_{ev_i}, check the following:
13: **does** the point c_i, $c_i \in RC_{ev_i}$, allow for a direct path towards d_{ev_i}, **if so:**
14: create a path νP_z, $z \in Z$, as $[s_{ev_i}, c_i, d_{ev_i}]$;
15: set the number of hops to 2;
16: find the trip distance of the path νP_z^l;
17: find the trip time of the path νP_z^t;
18: estimate the residual battery capacity, β_{ev_i}, at d_{ev_i};
19: update RC_{ev_i};
20: **else;**
21: point c_i allows for indirect path only towards d_{ev_i}, **and so**
22: find the current value of $\uparrow D_{ev_i}$;
23: repeat the steps 7 to 11 again;
24: find the next rely node c_j to d_{ev_i}, for which:
25: check if it allows for a direct path towards d_{ev_i}, **if so:**
26: create a path νP_z as $[s_{ev_i}, c_i, c_j, d_{ev_i}]$;
27: set the number of hops to 3;
28: find the trip distance of the path νP_z^l;
29: find the trip time of the path νP_z^t;
30: estimate the residual battery capacity, β_{ev_i}, at d_{ev_i};
31: update RC_{ev_i};
32: else;
33: get back to line 21 again,
34: **choose** the preferred navigation mode, and accordingly to sort RC_{ev_i};
35: select path νP_z that satisfies the chosen mode,
36: **output** the route at the EV's navigation screen,
37: **end;**

4 THE BENCHMARK MODEL

To validate our proposed model and assess its outcomes, we compare it with the proposal found in [11] that reads the EV's battery status at the trip's source point and accordingly finds the charging requirements for the running vehicle in particular. Based on that, as shown in Figure 2, it finds a threshold point called J on the traditional shortest path (i.e., the path that is chosen by the regular navigators for the fuel-running vehicles) towards the destination. Around that point, the model finds a charging station that feeds the EV with the required charge to continue its journey. This guarantees matching the real charge requirements of the running EV, but not through the shortest path for the whole trip.

Accordingly, they route the EV from its source point towards that threshold point J, and then from J towards the destination; forcing the route to pass through J in particular may not deliver the true shortest path for the whole journey. Certainly, as we will discuss next, if we let the model read the EV's battery status and accordingly find the candidate routes at the source point of the journey, then we may have a better chance to find the true shortest-matching path to the destination.

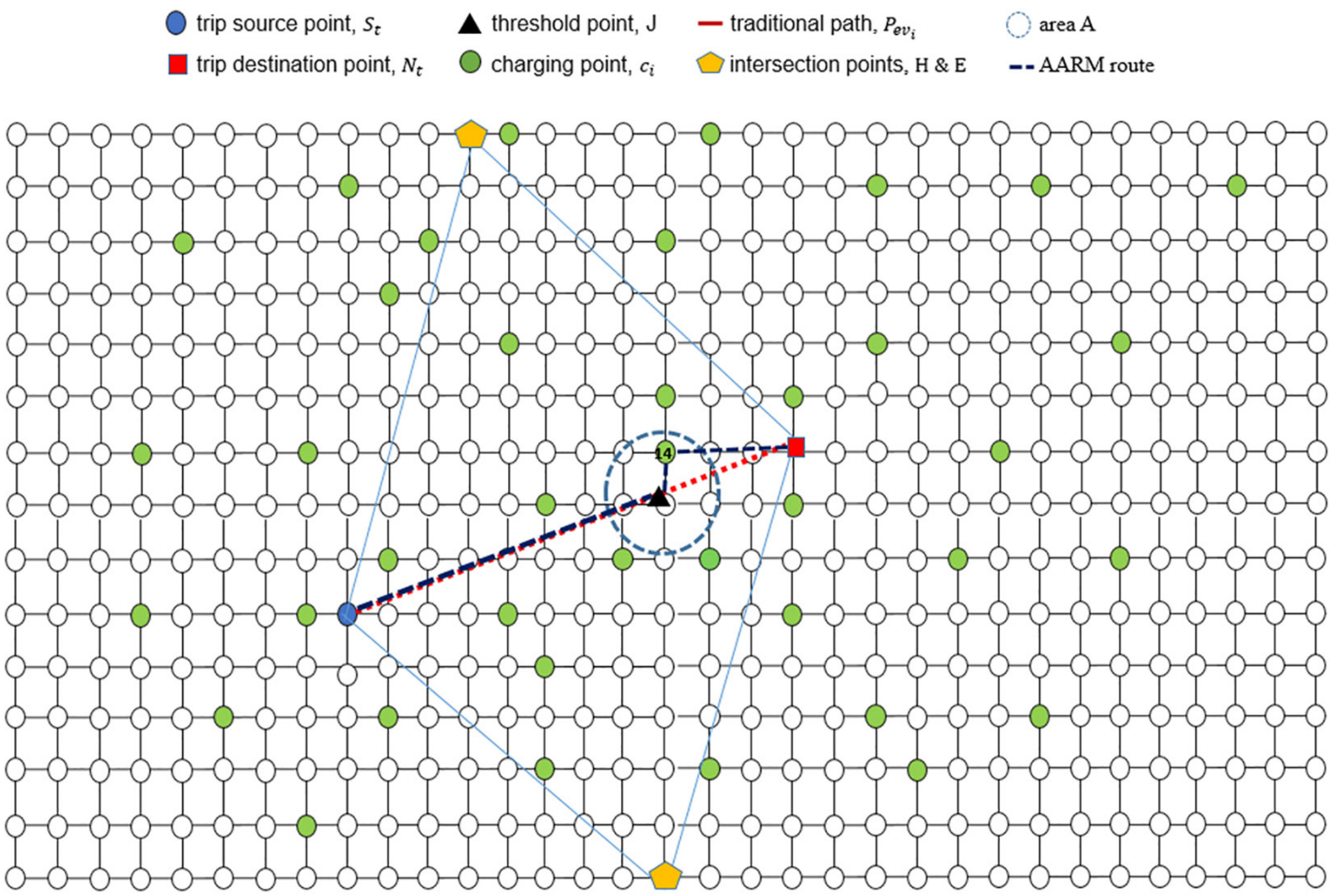

Fig. 2. AARM's route found through threshold area centered on point J [11]

Table 2 below presents the AARM algorithm proposed in [11], it summarizes their model's discussion, and as it is clearly noticed, the AARM model runs in an autonomous manner based on the trip's coordinates and the running EV status, besides being adaptive to any updates on the driving mode and any other updates related to the path selection process.

Table 2. The benchmark model, AARM, EVs' routing algorithm [11]

AARM's Model Routing Algorithm
1: ***input:** AARM model reads the EV type* θ_i, its SoH, and the EV's points S_t and N_t,
2: the current driving mode of the vehicle,
3: the battery charge status τ_{ev_i},
4: the power consumption rate of the vehicle in ρ_{ev_i},
5: **for** each EV type θ_i, and the Threshold value set by α;
6: Find the range threshold value $R^{thr}_{ev_i}$, and accordingly from the point S_t, find the location of point J,
7: Calculate the distance D, and around J create the circular search area A;
8: **run** AARM navigation, list candidate charging points c_i in L, and **then**
9: **while** the list L is not empty, **and** there is at least a c_i that is compatible with θ_i, then **do**;
10: For the source S_t, run Dijkstra $\forall\ c_i \in L$, and then:
11: according to path length, sort list L in an ascending order, update L,
12: select c_i with the shortest path length in L, update the route in the navigation system,
13: **else**;
14: shift the point J towards S_t by a distance of $D/2$,
15: create a new search area A',
16: **get back to** line 8 again,
17: being charged in c_i, start from line 1 again.
18: **end**;

5 SIMULATION RESULTS AND DISCUSSION

In this section, we are presenting samples of the results obtained from the simulation that we developed using the Microsoft Visual Studio and C++, in order to assess the performance of our proposed routing model. We chose the Visual Studio as it allows for a cross platform for efficient development environment to build C++ codes that go with varying systems and platforms. As a hypothetical test bed, we assumed having a geographical area like that shown in Figure 3, and as shown in the figure, we assigned a set of 25 charging stations, labelled A–to–Z, that are distributed all over the map to provide a kind of coverage to serve the electric vehicles.

These charging stations are assumed to provide compatible charging services for the different EVs' makes and models used in this simulation. Accordingly, over this area and through the assigned set of charging stations, we ran different navigation requests from three different types of EVs that are shown in Table 3. It is worth highlighting that the trips we run in our simulation can be from any node to any other node labeled A to Z in the map in Figure 3. However, although the nodes A to Z are charging points, they are not considered active charging points when chosen as either a trip's source or destination points.

Table 3. Simulated EVs of different makes and models*

Make	Model	Range with 100% SoH	Current Battery Charge
Nissan Leaf	2016	168 kms	80%
Volkswagen e-Golf	2018	190 kms	80%
EQA Mercedes Benz	2021	350 kms	80%

Note: *These values are only for simulation, and do not necessarily represent the accurate case in real life.

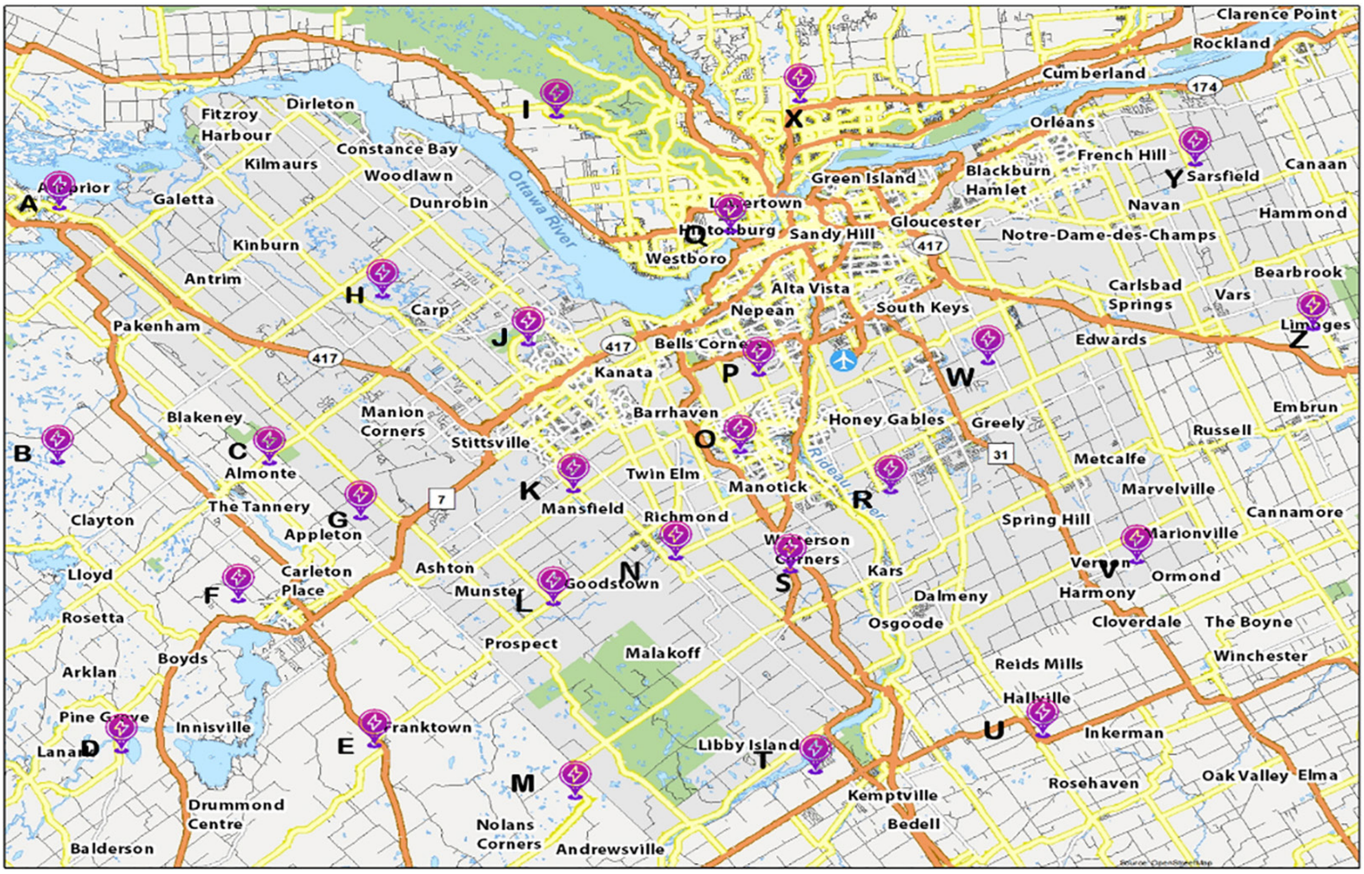

Fig. 3. A hypothetical geographical area with 25 EVs' charging stations

5.1 Discussion

From the simulation results, we aim to access the behavior of our proposed routing model, in this part, our discussion is extended to include varying navigation options (i.e. the drivers' routing preferences) provided by the proposed model, which include: (1) the trip's total distance, (2) the residual battery charge capacity at the trip's destination point, and (3) the time of the whole trip. It is worth to note that by considering different EVs from different makes and models, we are examining how autonomous our model is, and how it chooses the routing paths according to the running EV status and battery requirements.

Trips' total distance. To simulate the choice of shortest-path routing, for the same set of source-destination couples, we chose to run our proposed model for the three different EVs shown in Table 3. For these EVs, we also chose different SoH readings to show how it may affect the chosen trip paths. 90% SoH, 70% SoH, and 50% SoH. Accordingly, Figure 4 shows the resultant routes for six trips that we ran for the 2021 EQA Mercedes Benz EV between the following three different couples of source and destination points. In a (s_{ev_i}, d_{ev_i}) notation, and with reference to the map shown in Figure 3, those points are (Z, M), (I, Z), and (X, B).

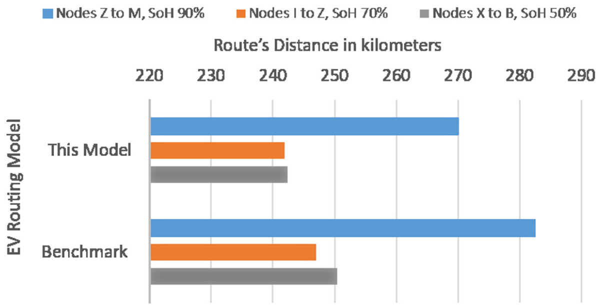

Fig. 4. Route lengths for 2021 EQA mercedes benz

It can be clearly noticed from the results shown in the figure that the routes obtained through the proposed routing model have shorter trip distances when compared to those of the benchmark model. This is also the case for the routes chosen by the 2018 Volkswagen e-Golf, whereas Figure 5 presents the routes with shorter or equal distances to drive when navigating using our proposed model compared to those of the benchmark ones. Getting equal distances is considered the worst-case scenario, and it happens only in the case that the benchmark's chosen route was by coincidence the shortest and, accordingly, will be the same route to find in the new model as well.

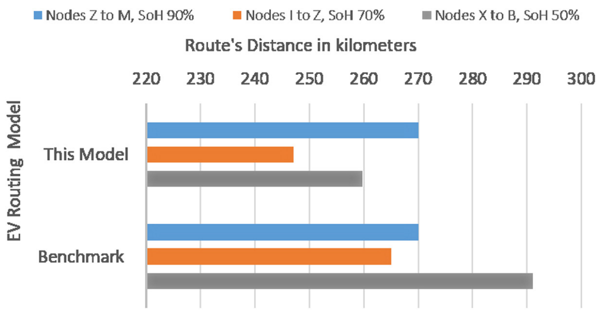

Fig. 5. Route lengths for 2018 Volkswagen e-Golf

As for the 2016 Nissan Leaf, in Figure 6, the model provides the following: a shorter route for the (Z, M) trip, an equal one for (I, Z), while for the trip of (X, B), our proposed model provides a route with 291 km for the whole trip, charging four times at the charging station points (Q, J, H, C), while no route is provided by the benchmark model for this particular trip. This is due to the fact that the 2016 Leaf originally came with a low battery range, which is only 168 km for a fully charged 100% SoH battery. In this run, the EVs are assumed to have only 50% SoH, which results in a very low range that limits the search space for candidate charging points according to the benchmark model and so results in no path being found towards destination point B.

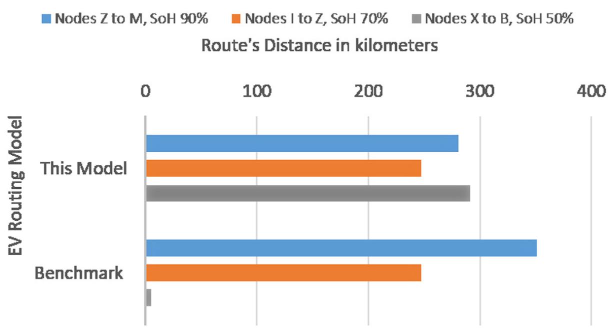

Fig. 6. Route lengths for 2016 Nissan Leaf

In this context, it is also worth checking the behavior of the proposed navigation model when reversing the couples of the trips' source-destination points. Figure 7 shows the results obtained for the 2016 Nissan Leaf when reversing the source and destination points for the same trips shown in Figure 6. The results are interesting; as an example, using the new proposed model resulted in: (1) A 280.41 km distance for the (Z, M) trip drives the EV via the routes Z, V, T, M, while it is 276.49 km when the trip's coordinates are reversed to (M, Z), routing the EV via M, S, R, Z. (2) Equal routes for both trips, (I, Z) and (Z, I) with a total distance of 247.11 km driving via the same route nodes. (3) A route of 291.15 km for the (X, B) via X, Q, J, H, C, B, and 277.09 km for the reversed one passing through B, C, H, I, X.

As for the benchmark model, the results show: (1) 351 km route for the (Z, M) trip, and 295.85 when reversed to (M, Z) passing through M, N,W, Z. (2) A route with 247 km for the (I, Z) trip via I, Q, W, Z, but no route for the trip when reversed! (3) There is no route for neither the (X, B) nor its reversed trip.

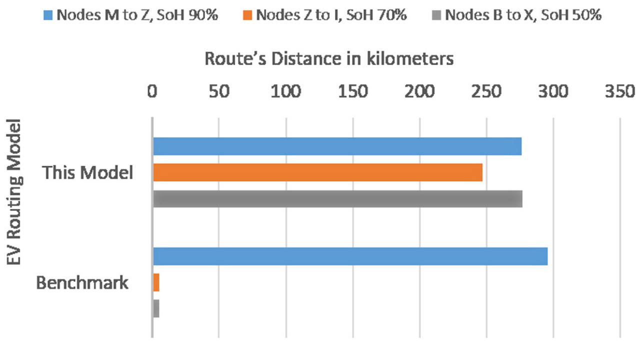

Fig. 7. Route lengths for 2016 Nissan Leaf, reversed trips

In this context, beside the comparison with the benchmark AARM model of [11], we also compared our proposed navigation model, AFARM, with that of [10], which adopts the polygon area navigation scheme. Among the simulation results, Figure 8 presents the navigation results of the three models for the (B, V) trip. As we can clearly see from the depicted results, the polygon model of [10] has the longest distance routes when compared to the other two models, both AFARM and the benchmark AARM models.

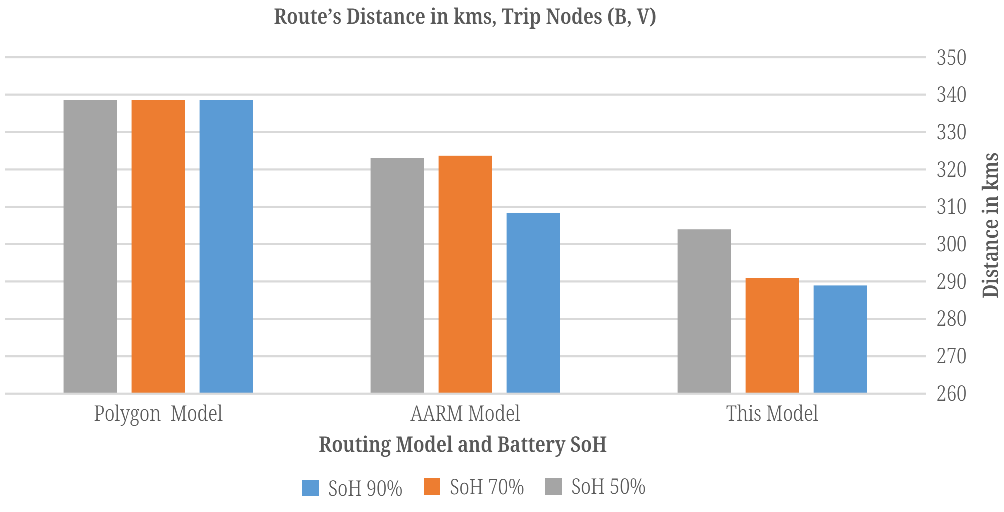

Fig. 8. Route lengths for the (B, V) trip, comparing polygon model, benchmark AARM, and AFARM

Moreover, the chosen paths of the polygon-based model in [10] are the same for the three EVs, which come with different SoH readings. This shows that such a model does not consider the EV's profile or its dynamic battery state. On the contrary, this is not the case for the other models; however, compared to the benchmark model of AARM, the results of AFARM show shorter routes for the same trip due to its different route lookup methodology being deployed.

Residual battery capacity. Driving an EV usually comes with a level of anxiety about being in "out of battery" status at the side of a highway waiting for towing! To help relieve such a level of anxiety, we proposed our model of routing to ensure driving the EVs via paths that suit their varying needs and specifications. This looks helpful, though we need to consider the fact that an EV needs to have a sufficient battery charge that allows starting a new trip after reaching the current destination point. Therefore, those EV navigation models need to consider this factor when processing their route requests.

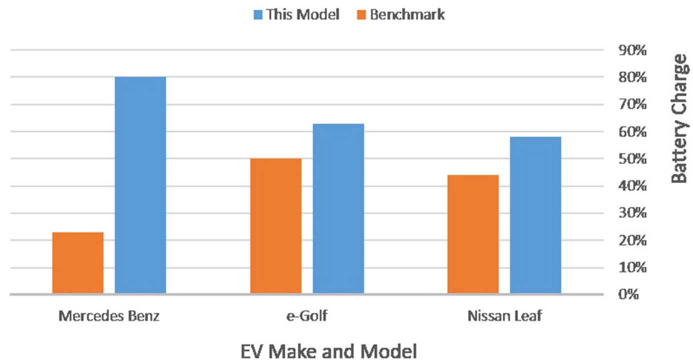

Fig. 9. Residual battery capacities for the (D, U) trip

Figure 9 shows a sample of the results obtained by the new proposed model for the residual battery capacities compared to those of the benchmark model. For the three types of EVs mentioned in Table 3, and for the trip (D, U), at the destination point U, the figure shows how the chosen routes of the proposed model allow for higher residual capacities, which allow the resumption of new trips with no anxiety or further concerns to worry about.

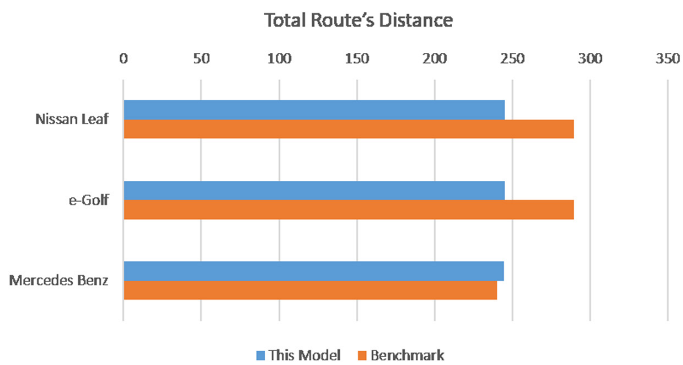

Fig. 10. Shortest trip distances for paths of max. residual capacities for the (D, U) trip

Figure 10 shows that such residual capacities come with shorter routes to drive by the 2016 Leaf and the 2018 e-Golf towards their destination. However, the results show a longer route (4.35 more km) for the 2021 Mercedes compared to that of the AARM, which could be justified by the fact that this run in particular did not seek for regular shortest routes but for the shortest distance-highest residual ones instead.

Trips' total time. In computer networks, the notation of least-cost routing may come with different interpretations based on the running routing protocol. In the same way, in our proposed model, beside the shortest trip distance option, we also allow the driver to choose the shortest trip time. This takes into account the route distance (i.e., the propagation time) and the number of charging points to stop by. The number of charging points on the route has a direct impact on the total trip time, as stopping by a station to charge the EV adds the charging time to the whole trip time. Having such an option may shorten the trip times; however, for EVs, reaching the trip destination points with sufficient residual capacities to start a new trip is considered important too. Therefore, in our proposed model, choosing the shortest trip times while maintaining the highest possible residual capacities is an allowed option for EV drivers. Accordingly, the drivers have the option to combine their preferences of having an anxiety-free and fastest route with a higher residual battery.

Figure 11 presents the resulting navigation times for the (D, U) trip with the running EVs having a battery SoH equal to 90%. As shown in the figure, the times for our proposed model are shorter for the Leaf and the e-Golf, but not for the Mercedes.

The route chosen by our proposed model for the Mercedes passes via D, T, U, with an extra 4.35 km compared to that of the AARM model, to ensure higher residual capacities by charging its battery at station T instead of going directly from D to U.

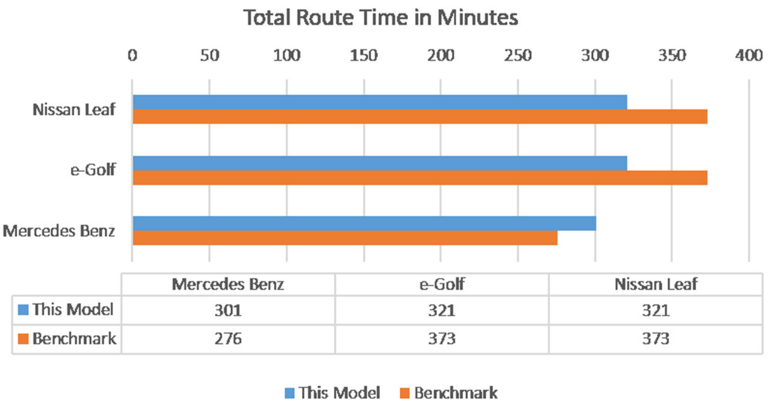

Fig. 11. Trip times for the route of maximum residual capacities for the (D, U) trip, with battery SoH = 90%

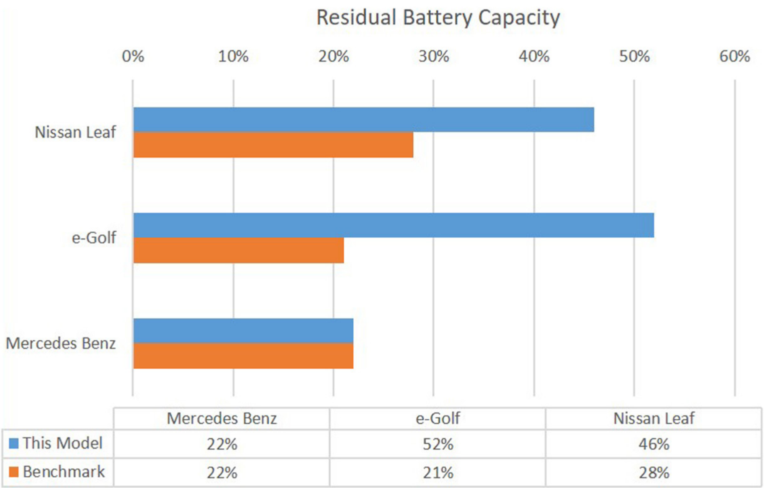

Fig. 12. Maximum residual capacities for the shortest trip times route of the (G, U) trip, with battery SoH = 70%

Figure 12 shows another example of routes, but for the trip of (G, U), in which we choose to find the shortest routes that attain the highest residual battery capacities while driving EVs, all with 70% SoH.

6 CONCLUSION

Climate change and its effects on health and environmental conditions, alongside the financial challenges the world is currently facing, have motivated the automobile industry to shift towards the EVs sector to address the aforementioned health and financial concerns. This looks promising; however, it creates new challenges that we need to tackle. Part of the challenge lies in making these new types of vehicles a truly convincing alternative to traditional fuel-powered vehicles. Battery range anxiety is considered one of the issues that hinders the adoption of such a green alternative by a large number of drivers. Routes in our country are well covered by fuel stations, in both urban and rural areas. However, this is not the case for electrical charging stations. Hence, in this work, we are proposing a model that can help alleviate the anxiety that EV drivers may feel when driving long distances, especially between or outside of cities. A navigation model specifically designed to cater to EVs. Compared to other models in the literature, our proposal's new contribution lies in two main aspects: First, it determines navigation routes based on the current status of the EV, taking into account factors such as battery charge and SoH. Therefore, different routes might be assigned to different vehicles even if they have the same source and destination points. Second, according to the EVs' battery SoH, at the trip's starting point, the model evaluate the complete set of candidate routes and selects the one that is guaranteed to be the shortest among all the other routes. Third, it also allows drivers to check for routes that provide high residual battery capacities at the trips' destination points. This is truly important as the EV needs to have sufficient charge capacity to start a new trip again. Furthermore, as the trips' total time of the strips is a potential routing metric to consider, this proposed model enables EV drivers to make that choice. Furthermore, it is designed to combine any of the aforementioned metrics together as well.

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8 CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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