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Multi-Module Range Anxiety Reduction Scheme for Battery-Powered Vehicles

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Abstract— **Limited battery capacity and long charging time resulting in what is known as range anxiety have been major obstacles to the widespread adoption of electric vehicles. In addition to running out of battery power, some drivers are also concerned about the amount of time required to recharge their batteries (i.e., time anxiety). This paper focuses on these problems, proposing a Multi-Module Range Anxiety Reduction Scheme. The proposed scheme takes into account traffic density on roadways to provide an accurate computation of energy consumption to charging stations in order to overcome the driver's concern of being stranded en-route. Furthermore, it addresses the driver's concern about completing the recharging process in either minimum energy or time. Simulations are conducted to test and validate the proposed scheme.**

I. INTRODUCTION

Electric Vehicles (EVs), powered completely by batteries, are friendlier to the environment as they emit no tailpipe pollution and have higher efficiency than conventional vehicles [1]–[3]. However, the limited capacity of power supply restricts the driving range of an EV, i.e., the maximum distance the EV can travel with a single battery charge. This further leads to Range Anxiety (RA), namely, the concern and fear of the EV's driver of not reaching a charging station before the vehicle runs out of energy [4]–[6]. Some research has been conducted to provide solutions to the problem of RA focusing on driving range estimation and optimal charging station deployment.

An extension of the Breadth-First Search algorithm is proposed in [7] to estimate the driving range of EVs using a simple energy consumption model. To predict the remaining driving range, [8] has integrated a particle filter with Markov Chain using probability distribution. A driving range estimation approach that classifies the process to rough and precise range estimation is introduced in [9], taking into account the vehicle's current location, remaining battery charge, and road network topology. In [10], an estimator is addressed to estimate the driving range of an EV using a residual usable energy computation model to precisely describe the present energy loss and available discharge capacity. A range anxiety optimization framework has been shown in [11] to reduce the probability of not completing a long trip by 5 percent, depending on driving conditions. In [12], an algorithm is proposed to assure that each driver can reach at least one charging station during any travel by comparing the battery charge the EV needs during any journey to the energy cost required to reach nearby charging stations.

A broad study about the RA phenomenon in [13] concludes that optimal charging station deployment would alleviate the effect of RA on drivers. An agent-based decision support system is introduced in [14] to allow strategic deployment of new charging stations in residential areas. Considering the problem of charging station deployment as an optimization problem, [15] has proposed a genetic algorithm using origin-destination data of fossil fuel-based vehicles. In [16], an integrated decision-making framework is presented to model a collaborative business between EVs' makers and charging station operators for optimal charging station deployment and operation.

Optimal routing under battery constraints has been an important research aspect of EVs. In [17], an algorithm is proposed to compute optimal-energy paths under battery constraints. A result by [19] has been employed by [18] to perform a preprocessing phase prior to finding optimal-energy paths in any road network. While a framework of the A^* search algorithm has been presented in [20] functioning to compute optimal-energy paths, [21] has introduced a path-finding algorithm, based on A^* search, that functions in energy and time modes under battery constraints. However, the optimality of one mode is neglected when computing the optimal path in the other mode. In addition, traffic density is not considered in either mode.

The objective of this paper is to develop a Multi-Module Range Anxiety Reduction Scheme (MRARS) based on the approach proposed in [12]. The scheme to be developed is aimed to periodically analyze the battery charge the EV needs to reach nearby charging stations to alleviate the drivers' concern of being in an out-of-energy state. It accurately computes the optimal-energy paths to all reachable charging stations, taking into consideration traffic density on the roadways. Moreover, the MRARS functions in two modes based on the driver's preference, i.e., energy mode vs. time mode, to cover the optimality of both energy and time in reaching nearby charging stations and completing the recharge of the drained battery.

This paper is divided into five Sections. Section II states the problem of reaching optimal charging stations based on the driver's preference. Section III introduces the proposed MRARS, which provides the EVs' drivers with the optimal charging stations to recharge their drained batteries.

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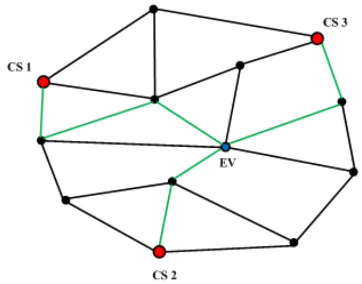

Fig. 1. A simple example of a road network with one electric vehicle (EV) and three charging stations (CS_1, CS_2, and CS_3)

Section IV presents simulation tests and reports results of investigating the performance of the MRARS. Finally, Section V provides concluding remarks and future research direction.

II. Problem Statement

Consider a road network represented by a directed graph, $G = (V, E)$ with n vertices, $V = \{v_1, v_2, \ldots, v_n\}$ and m edges, $E = \{e_1, e_2, \ldots, e_m\}$. Vertices in V represent nodes corresponding to road intersections and edges in E correspond to road segments. For each vertex $v_i \in V$, there is an elevation $u(v_i) \in R_0^+$, while each edge $e_j \in E$ has a length $l(e_j) \in R^+$ and average speed $S(e_j) \in R^+$. $S(e_j)$ is in inverse relationship with the traffic density $D(e_j)$ on edge e_j. Each edge $e_j \in E$ has a weight of energy cost EC_{e_j} with which $S(e_j)$ is in direct relationship. A path on G is defined as a sequence of k adjacent edges, $p = (e_1, e_2, \ldots, e_k)$. Consider a road network consisting of n vertices and m edges with c charging stations $CS = \{CS_1, CS_2, \ldots, CS_c\}$ assumed to be located at $v_{CS_b} \in V$ respectively, where $b = 1, 2, \ldots, c$. An example of such a network with three charging stations is illustrated in Fig. 1.

For this defined network, assume that at a certain time step t, the EV of interest at v_i received an alert of energy depletion. The optimal-energy charging station finding problem, in this setting, is to find a $CS_b \in CS$ that requires the minimum path-energy cost, EC_p. The optimal-energy path p_o in the set of all possible paths $P = \{p_1, p_2, \ldots, p_q\}$ to CS_b, is the one on which EC_p from v_i to v_{CS_b} is the minimum. However, if the traffic density D_j is not taken into account, every $e_j \in E$ will have the same $S(e_i)$; consequently, the weight values of EC_{e_j} will not be accurate. As a result, p_o computed from v_i to v_{CS_b} will not be accurate in its optimality, i.e., the actual optimal path, considering the traffic density, might be different from p_o.

The optimal-time charging station finding problem is to find the $CS_b \in CS$ that requires the minimum path-time cost, TC_p and waiting time T_{wb} at CS_b due to the queue length. The optimal-time path p_o in the set of optimal-energy paths $P_{oE} = \{p_1, p_2, p_3\}$ is the one on which the travel-time cost TC_p from v_i to v_{CS_b} is the minimum. Furthermore, searching a path that is optimal in time with the assurance of battery constraint satisfaction is not feasible in this case because such a path may not exist. Therefore, completing the battery recharge based on the driver's preference (i.e., energy or time) is a complex problem that requires intelligent technological solution.

III. Range Anxiety Reduction Scheme

The proposed Multi-Module Range Anxiety Reduction Scheme (MRARS) periodically analyzes the battery charge required by the EV to reach nearby charging stations during travel. It provides accurate path energy-cost computations to reachable charging stations by taking into account traffic density throughout the road network. In addition, it consists of two modules to cover concerns of energy and time in reaching charging stations and completing the battery recharge. The MRARS relies on real-time data of traffic and environment to produce the decision of reaching the optimal charging station based on the driver's preference. The logic used by the MRARS is depicted in Fig. 2. The energy-optimal path to every charging station is computed using the A^* search algorithm [22]. During travel, if the current battery charge depletes to reach a predefined threshold value, an energy shortage warning is displayed to assure the driver not to be stranded.

A. Energy Module

If the driver cares about saving energy more than time to complete the recharge of his/her drained battery, the optimal decision to make is following the energy-optimal path to the optimal energy-based charging station (i.e., the optimal energy-based charging station is the one with the minimum energy cost to reach). The path energy estimation model, introduced in [21], is developed to model traffic density by including a vehicle concentration variable to provide accurate path energy estimation.

1) Path Energy Estimation Model: As presented in [21], the problem of battery constraints is solved by modifying the A^* algorithm and dynamically adjusting the path energy cost such that optimal paths are only those having minimum energy cost and satisfying the battery constraints. The total energy cost of a path consists of different sub-costs as follows:

- Potential Consumed/Gained Energy: as the EV is travelling over an edge between two vertices a and b, the potential energy $EC_P(a,b)$ is consumed from the battery during the uphill travel and is gained into the battery during the downhill travel. The potential energy is given by [20] [21].

$$EC_P(a,b) = mg[(u(a) - u(b))] \tag{1}$$

  where m is the mass of the EV, g is the gravity factor, $u(a)$ is the elevation of vertex a, and $u(b)$ is the elevation

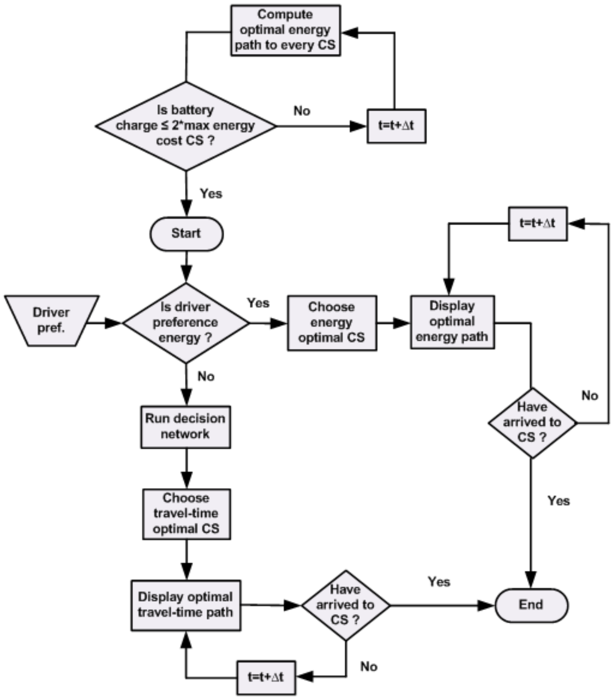

Fig. 2. Multi-module range anxiety reduction logic

of vertex b. In addition, $EC_P(a,b) > 0$ if $u(b) > u(a)$ and $EC_P(a,b) < 0$ if $u(b) < u(a)$.

- Loss of Energy: the loss of energy, which is always consumed from the battery, occurs due to aerodynamic and rolling resistances. It is given by [20] [21].

$$EC_{loss}(a,b) = f_r mgl(a,b) + \frac{1}{2}\rho A d_r S(a,b)^2 l(a,b) \quad (2)$$

where f_r is the friction coefficient, $l(a,b)$ is the length of edge (a,b), ρ is the air density coefficient, A is the cross sectional area of the EV, d_r is the air drag coefficient, and $S(a,b)$ is the average speed of traffic on edge (a,b).

- Acceleration/Deceleration Energy: the acceleration energy $EC_{ac}(a,b)$ is consumed from the battery as the EV accelerates to a higher speed while the deceleration energy $EC_{dc}(a,b)$ is recuperated and stored into the battery as the EV comes to a lower speed. They are given by [21].

$$EC_{ac}(a,b) = P_{wr} t_{ac} \quad (3)$$

$$EC_{dc}(a,b) = -P_{wr} t_{dc} \quad (4)$$

where P_{wr} is the power of the electric motor, t_{ac} and t_{dc} are the times that the EV spends in acceleration and deceleration respectively.

- Energy Consumed by On-Board Electric Devices: this energy is not path related and is consumed directly from the battery by the on-board electric devices such as air conditioner, windshield wipers, etc. It is given by [21].

$$EC_{ed} = \sum_{i=1}^{n} P_{ed}(i) t_{ed}(i) \quad (5)$$

where $P_{ed}(i)$ is the power withdrawn by electric device i and $t_{ed}(i)$ is the time that device i takes in use.
Therefore, the total energy cost on a path $P = (e_1, \ldots, e_k)$ is

$$EC(P) = \sum_{i=1}^{k} EC(e_i) \quad (6)$$

where $EC(e_i)$, the energy cost on e_i connecting any two vertices a and b taking into account the efficiency η of the EV's motor, is computed as

$$\begin{aligned} EC^*(e_i) = [&EC_P(e_i) + EC_{loss}(e_i) \\ &+ EC_{ac}(e_i) + EC_{dc}(e_i)] \end{aligned} \quad (7)$$

$$EC(e_i) = \begin{cases} \frac{1}{\eta} EC^*(e_i) & if \quad EC^*(e_i) > 0 \\ \eta EC^*(e_i) & otherwise \end{cases} \quad (8)$$

To model traffic density throughout a road network, we introduce the traffic density variable $D(e_i)$ to represent the vehicle concentration on edge e_i in *veh/km*. [23] justified the linearity of the relation between traffic density and speed under mild generic assumptions, concluding that as traffic concentration/density increases, speed decreases. As such, on road segment e_i, some definitions are stated.

- The maximum speed the vehicles can travel at, $S_{max}(e_i)$, will only occur when there are no other vehicles on the roadway and the minimum speed vehicles can travel at is zero, $S_{min}(e_i) = 0$.
- The average speed of traffic goes to zero as the road reaches the maximum density, $S(e_i)$ converges to 0 as $D(e_i)$ converges to $D_{max}(e_i)$

Therefore, considering a linear relation between the traffic density and average speed, the average speed of traffic on e_i with density $D(e_i)$ takes the form:

$$S_D(e_i) = S_{max}(e_i)\left(1 - \frac{D(e_i)}{D_{max}(e_i)}\right) \quad (9)$$

Proposition 1. *Consider an arbitrary road segment in the road network that is represented by $e_i = (a,b)$. Denote the maximum speed and density on e_i with $S_{max}(e_i)$ and $D(e_i)$ respectively. Assuming that the linear relation in (9) holds and the acceleration and deceleration times on e_i are equal, i.e., $t_{ac} = t_{dc}$, the energy cost $EC(e_i)$ on e_i is smaller for higher $D(e_i)$.*

Proof: (9) implies that higher $D(e_i)$ results in smaller $S_D(e_i)$. Hence, by (2), higher $D(e_i)$ leads to smaller $EC_{loss}(a,b)$. By (1), we have $EC_P(a,b)$ independent of $S_D(e_i)$. By (3) and (4), $EC_{ac}(a,b)$ and $EC_{dc}(a,b)$ eliminate each other since $t_{ac} = t_{dc}$. Therefore, by (8), higher $D(e_i)$ leads to smaller $EC(e_i)$.

□

B. Time Module

In case that the driver's concern of completing the recharge of his/her drained battery is time and not energy, the time module provides the driver with the optimal time-based charging station (i.e., the optimal time-based charging station is the one that requires the minimum costs of travel-time and waiting at the station among all the reachable charging stations). The time module relies on using a decision network, which is able to model congestion on roads and at charging stations.

1) Decision Network: Decision networks, which rely on the maximum expected utility principle, allow EVs to reason about their possible actions in choosing the optimal time-based charging station. They state that a rational EV should choose the charging station that maximizes its expected utility. If the EV has n possible states of the world, the expected utility Eu_i of taking a short path Sh_i to charging station CS_i, given evidenced information about the traffic density D_i on the path and queue length Q_i at CS_i, is

$$Eu_i(Sh_i|D_i,Q_i) = \sum_{j=0}^{n} p(w_j|Sh_i,D_i,Q_i)u_i(w_j) \qquad (10)$$

where $p(w_j|Sh_i,D_i,Q_i)$ is the probability of the state w_j given Sh_i, D_i, and Q_i. $u_i(w_j)$ is the utility function that values the possibility of state w_j to happen by mapping a numerical value to it.

Fig. 3 depicts the proposed decision network. In this network, the chance node L_i represents the delay that might happen during the battery recharge at CS_i where $i = 1,2,\ldots,c$. The chance node D_i represents the traffic density on the path leading to CS_i, while the chance node Q_i represents the queue length at CS_i. The decision node Sh_i represents the path distance to CS_i and whether it is short or not. Finally, the utility node U_i represents the utility function with the most desirable state given the highest value and the least desirable state given the lowest value as shown in Table I. The domains of the decision network variables are as follows:

$$dom(L_i) = \{lot, little, none\}$$
$$dom(Q_i) = \{long, short\}$$
$$dom(D_i) = \{high, medium, low\}$$
$$dom(Sh_i) = \{true, false\}$$

The probability tables of the random variables Q_i and D_i are set based on their domain values after receiving the real time information of traffic density and queue length, while the probability table of the random variable L_i is designed in advance. Among all the accessible charging stations, the most efficient time-based charging station to complete the battery recharge is chosen using Algorithm 1. The path leading to the optimal time-based charging station is then displayed to the driver to follow. In Algorithm 1, c is the number of available charging stations, DN is the decision network, and CS_{Opt} is the optimal time-based charging station.

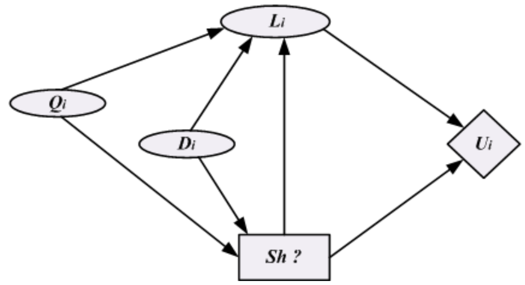

Fig. 3. A decision network to determine the optimal time-based charging station.

TABLE I
UTILITY FUNCTION TABLE

L_i	Sh_i	w_j	$u_i(w_j)$
Lot	$True$	w_1	30
$Little$	$True$	w_2	80
$None$	$True$	w_3	100
Lot	$False$	w_4	10
$Little$	$False$	w_5	40
$None$	$False$	w_6	70

Algorithm 1 Optimal time-based charging station selection

Input: CS_i, D_i, Q_i, Sh_i, where $i = 1,2,\ldots,c$;
Output: CS_{Opt};
  $i = 1$;
  $B = 1$;
  $u_i = u_i(L_i, Sh_i)$
  $Eu_i = DN(Sh_i, D_i, Q_i, u_i)$
  while $(i \leq c-1)$ **do**
    $u_{next} = u_i(L_{i+1}, Sh_{i+1})$
    $Eu_{next} = DN(Sh_{next}, D_{next}, Q_{next}, u_{next})$
    if $(Eu_{next} > Eu_i)$ **then**
      $B = i+1$;
    end if
    $i = i+1$;
  end while
  $CS_{Opt} = B$;

IV. Simulation and Results

Simulation was conducted to test and validate the performance of the MRARS. MATLAB was used to construct the test environment and conduct the simulation. A road network was constructed with 30 nodes, representing intersections, and 4 charging stations scattered randomly over a $30x30km^2$ area. Two different tests were performed. The first test compares the performance of the MRARS to the Range Anxiety Reduction Model (RARM), presented in [12], in terms of driving range. The second test investigates the performance

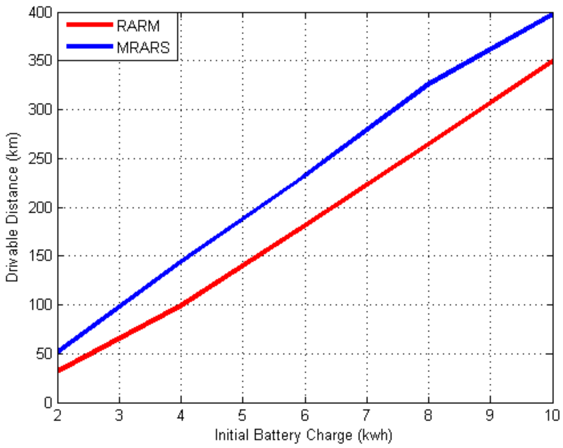

Fig. 4. Maximum driving distance with respect to initial battery charge

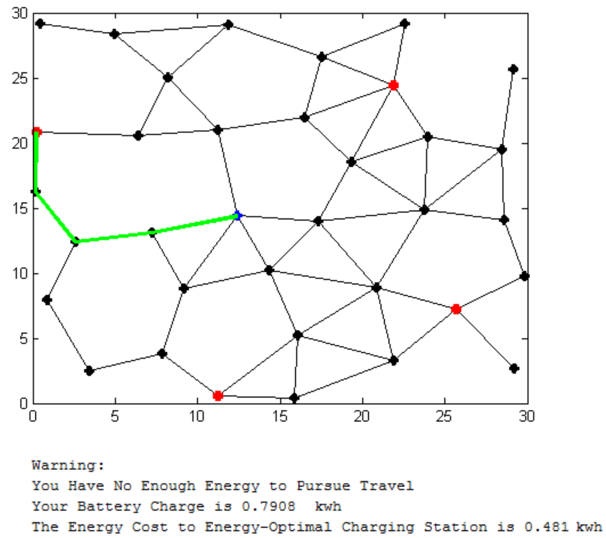

Fig. 5. Network and message of energy preference module

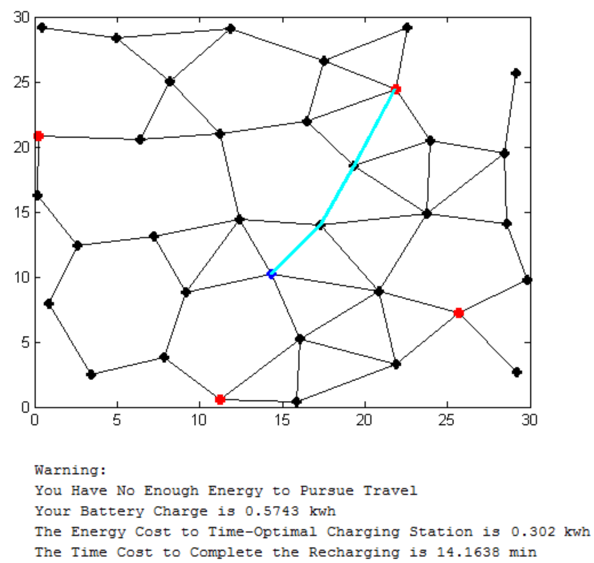

Fig. 6. Network and message of Time preference module

of the MRARS, assuming the driver's preference of either energy or time is known in advance, to reach a charging station and recharge the EV's battery.

To investigate the impact of modelling traffic density on energy consumption, for more than fifty runs, an EV was given initial battery charge and assumed to travel throughout the road network until it runs out of energy. Then, the maximum distance that the EV has traveled over is recorded. Fig. 4 shows the average maximum driving distance of five different runs achieved by the MRARS as compared to the RARM. It can be seen that the MRARS outperformed the RARM by achieving longer driving distances on average. When equipped with the RARM, the EV consumes more energy resulting in shorter driving range. This is because traffic density is not considered, assuming that all the road segments have an average speed of 60 $km/hour$. Conversely, when equipped with the MRARS, the EV consumes less energy and thus, achieves longer driving range. In this case, the roadways are given weights of traffic volume resulting in different average speeds in the range of 10 to 60 $km/hour$.

Fig. 5 illustrates the result obtained from running the MRARS based on the energy preference along with the message displayed to the driver. For more than twenty runs, the EV travelled throughout the road network until the battery charge reached the predefined low-energy threshold value. In all runs, the MRARS successfully provided the energy-based optimal charging station along with the energy-optimal path to follow. In Fig. 5, the charging stations are marked in red and the EV is marked in blue, while the energy-optimal path to the energy-based optimal charging station is marked in green. The energy-based optimal charging station, having index of 23 as shown in Table II, was chosen by the MRARS as it yields the minimum energy cost. The energy-optimal path is proven to be optimal by satisfying the admissibility and consistency conditions in the reduced positive energy-graph as shown in Table III.

TABLE II
ENERGY COSTS TO CHARGING STATIONS

Charging Station Index	23	4	35	3
Path Energy Cost in kwh	0.481	0.559	0.486	0.546

TABLE III
ADMISSIBILITY AND CONSISTENCY CONDITION SATISFACTION

Path Nodes	$g(kwh)$	$h(kwh)$	$f(kwh)$	Total Path Cost (kwh)
24	0	0.0949	0.0949	0.3404
12	0.1065	0.0719	0.1785	0.3404
2	0.1841	0.0606	0.2447	0.3404
30	0.2619	0.0323	0.2942	0.3404
23	0.3404	-0.0018	0.3385	0.3404

TABLE IV

RECHARGING TIME COSTS

Charging Station Index	23	4	35	3
Path Energy Cost *kwh*	Inf	0.291	0.326	0.302
Recharge Time Cost *Minutes*	Inf	23.676	22.131	14.164

Fig. 6 reports the result obtained from running the MRARS based on the time preference along with the warning of energy depletion displayed to the driver. For more than twenty runs, the EV travelled throughout the road network until the battery charge reached the predefined low-energy threshold value. In all runs, the MRARS was successful to provide the time-based optimal charging station along with the travel-time-optimal path to follow. In Fig. 6, the charging stations, assumed to offer the service of battery swapping, are marked in red and the EV is marked in blue, while the travel-time-optimal path to the time-based optimal charging station is marked in light blue. The charging station having index of 3 as summarized in Table IV was chosen by the MRARS to be the optimal since it requires the minimum total recharging-time cost. This charging station is not optimal in energy; however, it is guaranteed by the MRARS to be reachable with the current battery charge. In Table IV, the charging station having index of 23 was recognized by the MRARS not to be reachable with the current battery charge; therefore, its total energy and time costs were turned into infinity.

V. CONCLUSION

This paper has addressed the problem of driver anxiety which is recognized as a major obstacle to the widespread adoption of Electric Vehicles (EV). A Multi-Module Range Anxiety Reduction Scheme (MRARS) was proposed to reduce the concern and fear of EVs' drivers of running out of energy during travel. It assures the EVs' drivers not to be stranded by periodically comparing the path energy-costs to nearby charging stations with the current battery charge. The MRARS provides accurate computations of energy-optimal paths to charging stations by taking into consideration traffic density throughout the road network. In addition, it consists of two modules to cover the drivers' concern of completing the battery recharge based on both minimum energy and time costs. The performance of the MRARS was compared to a Range Anxiety Reduction Model (RARM) in terms of driving range. It was shown that the MRARS outperformed the RARM, achieving less energy consumption and thus longer driving range. The future direction of this research will focus on investigating the performance of the MRARS in real life experimentation.

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