A Time and Energy Efficient Routing Algorithm for Electric Vehicles Based on Historical Driving Data

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***Abstract*—A routing algorithm that leads to extended driving range and battery longevity of electric vehicles (EV) is proposed. In addition to locating the time and energy efficient routes, the proposed algorithm provides a desired speed profile to be tracked by the driver. Data mining techniques are employed for extracting the desired speed profile for the goal driver from a set of historical driving data. In order to select data with strong analogy to those of the goal driver's vehicle and driving conditions, driving and vehicle attributes are defined. The historical driving data are clustered and the class of the goal driver among clustered data is determined through classification. Eventually, the required travel time and energy consumption corresponding to historical speed profiles are evaluated and the time and/or energy efficient route along with the desired speed profile are determined. The proposed method is tested on a set of data gathered in the Warrigal project, which provides real vehicle state information. Since the consumed energy data are not available in this dataset, a detailed EV model is adopted to estimate the energy consumption. The obtained results verify the effectiveness of the proposed routing algorithm in locating the time and/or energy efficient routes.**

***Index Terms*—Classification, clustering, data mining, efficient routing, electric vehicle (EV), energy consumption, travel time.**

I. Introduction

INTELLIGENT transportation systems (ITS) could potentially provide solutions to numerous problems raised by growing number of vehicles such as, frequent traffic congestions, air and noise pollution, and high dependency to fossil fuels [1], [2]. One of the main functions of ITS is to provide routing services which aims at finding a route to meet certain objectives, such as reducing the travel time, traffic congestion, consumed energy, and emissions [3].

Traditional problem of finding the shortest path in a graph has been extensively addressed for stationary and nonstationary stochastic networks in the literature. It is demonstrated in [4] that an efficient Dijkstra-type algorithm can be employed to find the minimum cost route in a stationary stochastic network. In traditional Dijkstra algorithm, routing concentrates on finding shortest paths in networks with positive and static edge costs representing the distance between two nodes [5], [6]. For a nonstationary stochastic shortest path problem, AO$*$ is introduced in [7] as an efficient solution.

Unlike optimal routing algorithms for conventional vehicles in which the main goal is normally to find a route with minimum travel time, for electric vehicles (EV), choosing an energy-efficient route is of high importance. Furthermore, due to recuperation characteristics of EVs, the edge cost defined for routing algorithms would not be nonnegative and as a result, most commonly used shortest-path algorithms cannot be employed for EV routing purposes.

In [8], the constrained shortest path (CSP) algorithm is employed for EV energy optimal routing. Maximum and minimum capacity of battery are considered as constraints to avoid negative edges (links). Also, the graph is extended by creating a vertex for every preceding link with distinct velocity, and dynamic energy cost caused by acceleration and deceleration due to different speeds of two successive links is considered. In [6], battery constraints and energy are incorporated into edge cost of the road network and an A^* heuristic algorithm is proposed to find the energy-efficient route. However, the considered energy cost, which consists of potential energy and energy loss, requires accurate knowledge of vehicle parameters and roadway conditions. In addition, energy cost of transitioning from one link to another is not taken into account.

A dynamic route planning method is proposed in [9] which takes the real-time traffic condition into account. Also, a model for calculating EV energy consumption is presented and a constrained A^* algorithm is proposed for route planning purposes with time and energy efficiency objectives. In [10], a multi-criteria routing algorithm based on A^* is proposed that operates in energy-optimal or time-optimal modes and under battery constraints.

In [11], an EV model is presented and the problem of negative path costs generated by regenerative braking is solved by employing Bellman-Ford method, which is a deterministic optimization approach. In that study, speed is assumed equal to speed limit throughout a link. Also, energy calculation for each link is carried out online, which leads to considerable computational burden. Similar to [11], the Bellman-Ford approach is used in [12] for eco-routing of EVs. The average speed is considered as the speed throughout a link, and acceleration at the interface between adjacent links as well as an additional acceleration for critical road infrastructure elements are taken into account.

In [13], the problem of EV routing is solved by a mixed integer model with a piecewise linear objective function and by

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considering battery constraints, load capacity and time windows. Also, speed throughout a link is determined based on the average speed in each segment during different time intervals.

A particle swarm optimization method is proposed in [14] to find the most energy efficient route between two points. To calculate energy consumption, all dynamic and static factors affecting the energy consumption are considered; however, important components such as electric machine, dc-dc and dc-ac converters and model of battery is not considered in the energy consumption calculations. In addition, speed and road slope are considered constant within a segment.

Recently, researchers have incorporated additional objectives and constraints to the routing problem. In [15], a multi-objective route planning algorithm is proposed for solar-powered EVs. The algorithm aims at finding a route for maximum solar power collection and with minimum travel time and energy consumption. In [16] and [17], eco-friendly navigation systems are proposed for extending the battery lifetime and driving range. In those algorithms, the effect of route behavior and HVAC power consumption are considered.

By incorporating grid-to-vehicle and vehicle-to-grid services to the routing problem, a multi-variant route optimization model for EVs is presented in [18]. The variants include fast charging, slow charging, discharging, time windows, pickup and delivery, dynamic rates, and stochastics demand. In [19], EV routing for multiple depots and charge stations is carried out by optimization of EV expenses. Also, practical constraints such as, real-time electricity price, battery capacity, vehicle load capacity, customer delivery/pick demands, customer time windows, battery and vehicle life-lost cost and charge station/customer service time are considered.

In all of the abovementioned studies, the speed throughout each link is considered constant and equal to the speed limit or the average speed in the link. However, vehicles speed in a path mainly depends on the traffic level, and not solely the speed limit. Furthermore, link slopes are considered constant. It is noteworthy to mention that without having knowledge about speed variations throughout a link, choosing it as an energy efficient path is incorrect. This is due to the fact that cruising speed, decelerations, and accelerations impact the energy consumption the most significantly.

In [20], dependency of energy consumption on vehicle characteristics, speed and route is studied. In addition to assumption of constant link speeds and slopes, only maximum travel time is considered as the constraint in the developed routing algorithm. Number of papers that focus on finding EV optimal speed based on the vehicle model is very limited and those which study this subject [21], simplify their methodology by, for instance, neglecting the roadway conditions.

In this paper, a routing algorithm for EVs, which is capable of finding a time and/or energy efficient route along with an efficient speed profile, is proposed (see Fig. 1). The proposed algorithm aims at meeting two different objectives. First, to find a route with the shortest travel time since for some drivers, energy-efficient routing might be desirable only if they reach their destination in a short period of time [22]. As the second objective, the algorithm yields an energy efficient route and a speed profile for reducing energy consumption in EVs.

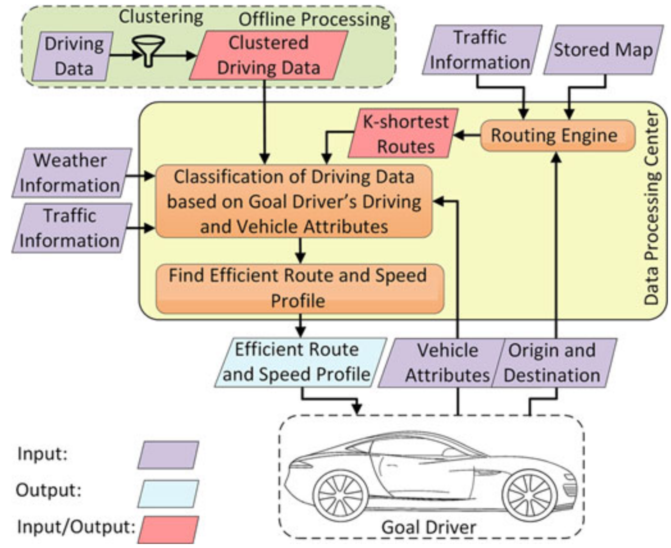

Fig. 1. Outline of the proposed routing algorithm.

The major contributions of the paper can be summarized as follows

1) A detailed model of an EV is developed to calculate energy consumption when such data is not available.
2) A routing algorithm for time and/or energy-saving in EVs, which employs historical speed profiles and takes into account the environment, roadway and traffic conditions, is proposed.

Unlike most intelligent learning techniques, which require availability of historical speed profile for the goal driver, the proposed routing algorithm uses the available speed profiles of other drivers with similar, rather than the exact same, driving conditions. A case study using real data is carried out to validate the effectiveness of the proposed routing algorithm in locating time and energy efficient routes.

II. Problem Description and Outline of the Proposed Routing Algorithm

A. Energy Efficient Route and Driving

It is important to highlight the difference between energy efficient route and energy efficient driving. Energy efficient route is determined based on roadway characteristics, such as road type and vertical grade, and traffic conditions, such as congestion level and speed limits. Energy efficient driving is adjusting the speed by taking the vehicle characteristics as well as environmental, roadway and traffic conditions into account, such that the consumed energy is minimized. Hence, energy consumption of an EV would be minimized if the driver takes the energy efficient route while driving energy efficiently. As a result, these two factors must simultaneously be taken into account in the EV routing algorithm.

B. Glossary

The following terms are frequently used throughout the paper

1) *Goal driver*: The driver that intends to use the routing algorithm.

2) *Segment*: A portion of a facility between two nodes (points).
3) *Node (Point)*: A place along a facility where segment capacity changes significantly, regulated by a traffic control device or traffic streams cross, merge or diverge [23].
4) *Database Center*: A center with huge storage capacity and computational power which can communicate with vehicles.
5) *Historical Driving Data*: A set of data including historical speed profiles (driving cycles) throughout a segment, driving conditions of that segment and characteristics of the EVs that have travelled through that segment.
6) *Driving and vehicle attributes*: Attributes (features) such as vehicle and cargo mass, temperature, traffic condition, travel time period and the vehicle power that express the driving conditions and the vehicle's characteristics, which are used as attributes for classification of historical speed profiles. These attributes, which will be explained in detail in Section V, are effective factors in the EV energy consumption and speed profile tracking.
7) *Candidate Routes*: A set of shortest-time routes among all available routes connecting the origin and destination of a trip. Candidate routes are investigated and one of them is selected as the time and/or energy efficient route.
8) *State of Charge (SoC)*: A measure of existing energy in battery and is defined as the ratio of the battery's current capacity to its full capacity.

C. Outline of the Proposed Routing Algorithm

Fig. 1 depicts the outline of the proposed routing algorithm. The main idea of the algorithm is to estimate the required time and energy for travelling from an origin to a given destination through all the available routes and select a time and/or energy efficient route with the corresponding speed profile. The travel time and energy consumption are estimated based on historical driving data of other drivers, rather than the goal driver. In order to obtain reasonable results, there must be a strong analogy between the goal driver's and other drivers' driving conditions and their vehicles characteristics. To meet this requirement, driving and vehicle attributes (features) are defined and used in the proposed routing algorithm. First, the available historical driving data are clustered and then, by using classification methods, the class of the goal driver among clustered data is determined. In Section V, application of data mining techniques for the proposed routing algorithm is discussed.

III. Proposed Routing Algorithm

A. Objectives of the Proposed Routing Algorithm

Finding a route with the shortest traveling time has been the priority of drivers when they use routing services [24]. This issue has been considered in numerous routing algorithms in the literature. One may think that a considerable amount of time is needed for charging EV's battery and consequently, reducing energy consumption can save the driver's time in this manner. However, many drivers recharge their EVs at night.

There are some exceptions that energy saving is turned into the main priority, though. For instance, there could be a situation where a route with minimum travel time may derive the battery out of energy. In this case, the driver should take a route that he/she is confident in arriving at his/her destination without running out of battery charge, or at the worst-case scenario, the route that leads to a charging station. In addition, there are situations that the driver can save a considerable amount of energy at the expense of taking slightly longer trips. As a result, two objectives must be taken into account in the EV routing algorithm: first, to find a route with minimum travel time, and second, to find a route that leads to minimum energy consumption.

By considering these goals, the output of the algorithm is to locate a route and generate a speed profile (speed as function of position) which will result in reduced travel time and/or consumed energy. For the remainder of the paper, this algorithm is referred to as the efficient routing algorithm.

B. Assumptions

The following assumptions are made in the proposed algorithm

1) Each vehicle is equipped with required measuring and communication devices to gather the required data and transfer them to the database center.
2) Initial required data for the algorithm including satellite maps, real-time traffic data, temperature and roadway conditions, such as speed limits, are available in the database center.
3) EVs are equipped with speed control system so that the vehicle's speed can be adjusted based on the obtained speed profile from the routing algorithm.
4) The driver and vehicle's sensors dictate the speed in special occasions.
5) Available maps in the database center consist of N nodes connected to each other by a set of segments denoted by S.
6) At the end of each travel by an EV, speed profile and its corresponding energy consumption profile, vehicle attributes, nodes passed by the EV and SoC are transmitted to the database center and stored. Afterwards, driving condition is determined based on the time and route of travel, and traffic information. If energy consumption and SoC are not available, they can be estimated based on speed profile and vehicle's characteristics (see Section IV), which are available in the database center. A specific code can be assigned to each vehicle model and type and the vehicle's manufacturer can provide this information for the center. If the information is unavailable, it can be estimated from other vehicles in the same class.
7) Driving data that are noisy or violating traffic rules, such as speed limits, are removed or modified before being used in the algorithm.

C. Proposed Routing Algorithm Framework

Based on the abovementioned assumptions, the routing algorithm shown in Fig. 2 is developed. The proposed algorithm is explained as follows

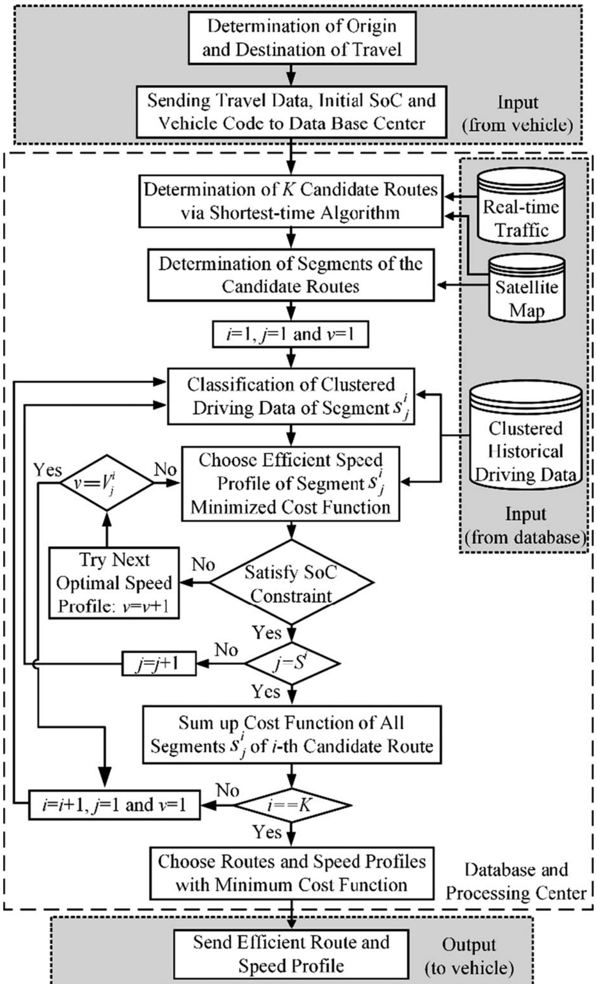

Fig. 2. Flow chart of the proposed routing algorithm.

1) The trip origin and destination is determined by the goal driver. Origin node is denoted as O and the destination node as D.
2) Vehicle code, initial SoC of battery and trip data, including origin and destination of the trip, are sent to the database center.
3) In the database center, based on available online maps, real-time traffic data and historical driving data, a set of routes with shortest travel time from node O to node D are located and introduced as candidates for the routing algorithm. Current navigation systems use common K shortest-time routes algorithms for this purpose [25], [26]. Note that, as discussed before, the travel time has the priority to energy efficiency; hence, the shortest-time routing algorithms are employed for finding the candidate routes.
4) Assume that K candidate routes exist and s^i is the set of segments through the i-th candidate route. If the number of segments in s^i is denoted by S^i, for $j = 1 : S^i$ the following steps are repeated:
   4–1) For s_j^i, i.e., the j-th segment of the i-th candidate route, a classification method is applied to the previously clustered historical driving data. In this manner, the class which contains driving data with attributes similar to those of the goal driver is selected (see Section V). v_j^i is considered as the set of historical driving data existing in the selected class of s_j^i. The number of data sets in v_j^i is denoted by V_j^i.
   4–2) After determining the goal driver's class, the desired speed profile through each segment is obtained. Based on historical speed profiles in the same class, as the first approach, the speed profile leading to the minimum value of a certain cost function, e.g., travel time or energy consumption or both, can be selected as the desired speed profile. As an alternative, the average of historical speed profiles in each segment can be considered as the desired speed profile. Although following such a speed profile is more feasible, energy savings may not be as significant as compared to the first approach.
   4–3) It is verified whether the selected speed profile satisfies the constraints or not. In this study, the minimum and maximum levels of SoC are considered as the constraints. If the constraints are satisfied, the solution is saved; otherwise, the next desired speed profile is chosen and the constraints are examined for it. If none of the existing speed profiles meet the constraints, the current segment must be eliminated from the route. Also, the routes that contain this segment must be removed from the pool of candidate routes. Similar procedure can be adopted if the average of speed profiles is selected as the desired speed profile.
   4–4) After obtaining the desired speed profiles and their corresponding cost functions for all the segments in a candidate route, its cost function value is calculated by summing up the cost function values of all its segments.
5) Step 4 is repeated for $i = 1$: K.
6) The efficient route is the route that has minimum cost function value among all candidate routes.
7) The efficient route and speed profile are communicated back to the vehicle.

IV. Electric Vehicle Modeling

The battery voltage and current in EVs are consistently measured for control purposes. Therefore, the energy drawn from the battery, i.e., energy consumption, would be available if voltage and current data were recorded and sent along with the speed profiles to the data processing center. Since such data were not available in this study, an EV model is developed to facilitate calculation of energy consumption corresponding to the speed profiles. Another purpose of the developed model is to bold the factors that have the most significant impact on EV energy consumption. Existing models in the literature are not detailed and most of them do not represent a comprehensive picture of an EV

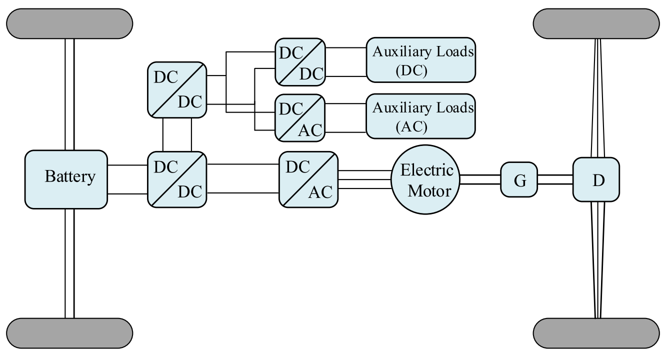

Fig. 3. Typical power system architecture of an EV.

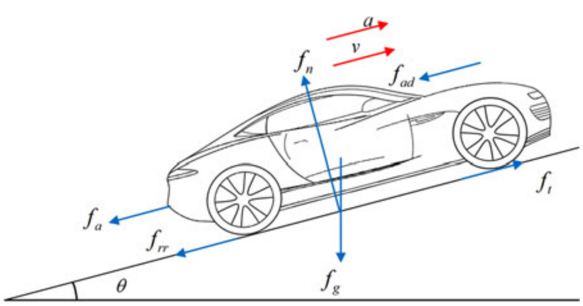

Fig. 4. Free body diagram of the forces acting on a vehicle.

power system architecture [8]–[14]. Fig. 3 depicts an EV power system architecture. In this section, details on modeling all the forces that act on a vehicle as well as the parts that consume bulk of the power in an EV are discussed.

A. Force Modeling

Bulk of the battery energy is consumed for traction. The amount of consumed energy can be estimated by using the traction force [27]. The forces that act on a vehicle, i.e., inertial force, wheels rolling resistance force, aerodynamic force and gravitational force, are shown in Fig. 4. Traction force, f_t, of a vehicle can be calculated as

$$f_t = f_a + f_{\text{gx}} + f_{\text{rr}} + f_{\text{ad}} \tag{1}$$

where, f_a, f_{gx}, f_{rr} and f_{ad} are inertial force, gravitational force, rolling resistance force of wheels and aerodynamic force, respectively. These forces are calculated as follows

$$f_a = ma \tag{2}$$

$$f_{\text{gx}} = f_g \sin\theta = mg\sin\theta \tag{3}$$

$$f_{\text{rr}} = C_{\text{rr}} f_n = C_{\text{rr}} mg\cos\theta \tag{4}$$

$$f_{\text{ad}} = \frac{1}{2}\rho_{\text{air}} A_f C_d (v + v_{\text{wind}})^2 \tag{5}$$

Here, m, a, g, A_f, C_d, v, v_{wind} and ρ_{air} denote the vehicle's mass, vehicle acceleration, earth-surface gravitational acceleration, vehicle frontal area, aerodynamic drag coefficient, vehicle speed, head wind speed and the air density, respectively. In addition, C_{rr} is the rolling coefficient and is obtained by [28]

$$C_{\text{rr}} = 0.01\left(1 + \frac{3.6}{100}v\right) \tag{6}$$

In (3) and (5), $0 \leq \theta \leq \pi/2$ is the roadway slope angle which can be obtained from available maps. In the case that the slope angle is not accessible, it can be calculated by the vehicle's position information as follows

$$\theta = Sin^{-1}\left(\frac{\Delta h}{\Delta d}\right) \tag{7}$$

where, Δh and Δd are the altitude and distance variations, respectively.

B. Transmission Modeling

The driving wheels torque, T_t, and traction power, P_t, can be obtained by using the calculated traction force as follows

$$T_t = f_t r_w \tag{8}$$

$$P_t = f_t v = T_t \omega_w \tag{9}$$

where, r_w is radius of the wheels and ω_w is the wheels angular velocity. Eventually, the shaft torque, T_s, can be calculated as follows [28]

$$T_s = \begin{cases} \eta_{\text{TS}} \frac{T_t}{G}, & P_t < 0 \\ \frac{T_t}{G\eta_{\text{TS}}}, & P_t \geq 0 \end{cases} \tag{10}$$

where, G denotes differential gear ratio and $0 \leq \eta_{\text{TS}} \leq 100$ is the transmission efficiency. Negative P_t occurs during regenerative braking. In this operating mode, which takes place during deceleration or when the vehicle runs downhill, the propulsion motor operates as a generator and electrical energy is fed back to the battery.

Shaft angular speed, ω_s, and power, P_s, can be obtained as follows

$$\omega_s = G\omega_w \tag{11}$$

$$P_s = T_s \omega_s \tag{12}$$

Shaft propulsion force is produced by the electric motor. For the sake of simplicity and also lack of knowledge about the propulsion motor parameters, its power can be calculated using the following equation

$$P_m = \frac{P_s}{\eta_m} \tag{13}$$

Here, P_m and $0 \leq \eta_m \leq 100$ are the propulsion motor power and its efficiency, respectively.

Power of the inverter, P_{inv}, that feeds the propulsion motor can be obtained as follows

$$P_{\text{inv}} = \frac{P_m}{\eta_{\text{inv}}} \tag{14}$$

where, $0 \leq \eta_{\text{inv}} \leq 100$ is the inverter efficiency.

C. Auxiliary Loads

In addition to supplying the required energy for traction, the battery is responsible for providing energy for EV auxiliary

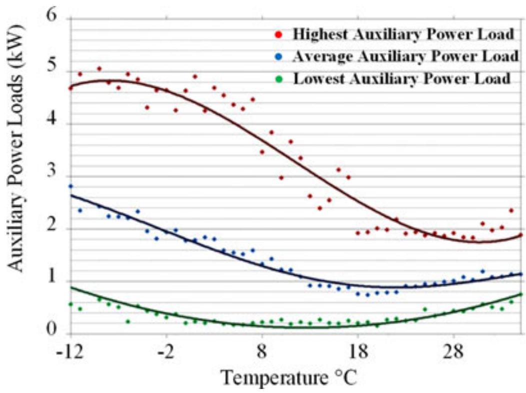

Fig. 5. Auxiliary power loads vs temperature for Nissan Leaf [31].

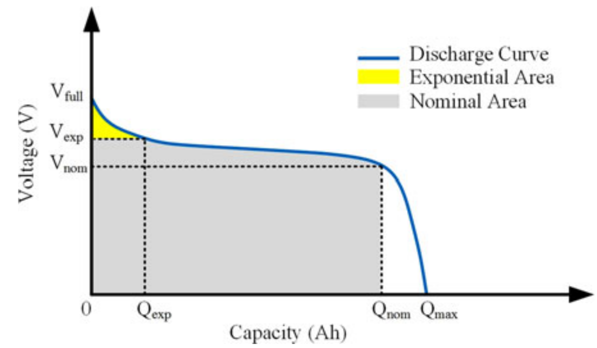

Fig. 6. Typical discharge characteristic of Li-Ion battery.

loads, as well. Auxiliary loads include heating, ventilation and air conditioning (HVAC) systems, headlights, power steering, communication systems etc. Very few number of existing models in the literature consider all the auxiliary loads and majority of them consider a constant, temperature-independent energy consumption by the HVAC system [10], [28]–[30]. In this paper, real data obtained from measuring consumed power by auxiliary loads in a Nissan Leaf through 7375 trips are used. Fig. 5 illustrates variations of auxiliary loads average power versus temperature. Such a plot can be obtained for any specific EV and used for estimating the auxiliary loads energy consumption.

Considering Fig. 3 as the power system architecture of an EV, DC-link power, $P_{\rm DC}$, and current, $i_{\rm DC}$, can be derived as

$$P_{\rm DC} = P_{\rm inv} + P_{\rm aux} \tag{15}$$

$$i_{\rm DC} = \frac{P_{\rm DC}}{v_{\rm DC}} \tag{16}$$

where, $P_{\rm aux}$ is the auxiliary load power and $v_{\rm DC}$ is the DC-link voltage. $v_{\rm DC}$ is maintained at a reference value by the DC-DC converters.

D. Battery Modeling

Generally, a boost DC-DC converter is used to interface the EV battery with the DC-link. The duty cycle of such a converter, $0 \leq d \leq 1$, can be obtained from [27], [32]

$$d = 1 - \frac{v_{\rm batt}}{v_{\rm DC}} \tag{17}$$

in which, $v_{\rm batt}$ is the battery voltage. The battery current, $i_{\rm batt}$, and cell current, $i_{\rm cell}$, are then calculated as follows [27], [32]

$$i_{\rm batt} = \frac{i_{\rm DC}}{(1-d)\eta_{\rm dc}} \tag{18}$$

$$i_{\rm cell} = \frac{i_{\rm batt}}{N_p} \tag{19}$$

Here, $0 \leq \eta_{\rm dc} \leq 100$ is the DC-DC converter efficiency and *Np* is the number of cells of the battery wired in parallel. The most commonly used battery technology in recent EVs is Li-Ion due to its longer life-span and shorter charge time. Therefore, a Li-Ion battery is considered in this paper and its modified Shepherd model [33] is employed in the EV model. A typical discharge curve of a Li-ion battery, which entails three regions, is illustrated in Fig. 6. If the battery filtered current is less than zero, i.e., $i^*_{\rm cell} < 0$, the cell voltage, $v_{\rm cell}$, can be formulated as follows by neglecting the cell internal resistance variations during charging and discharging cycles [33]

$$v_{\rm cell} = E_0 - Ri_{\rm cell} - \left(\frac{KQ}{it - 0.1Q}\right) i^*_{\rm cell} - \left(\frac{KQ}{Q - it}\right) it + A\exp(-B.it) \tag{20}$$

where, *it* is extracted capacity. If $i^*_{\rm cell} > 0$,then

$$v_{\rm cell} = E_0 - Ri_{\rm cell} - \left(\frac{KQ}{Q - it}\right) i^*_{\rm cell} - \left(\frac{KQ}{Q - it}\right) it + A\exp(-B.it) \tag{21}$$

A, E_0, *K*, *Q*, *R* and *B* are exponential voltage, cell constant voltage, polarization constant, cell maximum capacity, cell internal resistance and exponential capacity variables, respectively, and can be obtained from the battery datasheet.

The battery voltage can be then obtained using the following equation

$$v_{\rm batt} = N_s v_{\rm cell} \tag{22}$$

where, N_s indicates the number of cells in series. The battery power, $P_{\rm batt}$, can be calculated by

$$P_{\rm batt} = v_{\rm batt} i_{\rm batt} \tag{23}$$

Eventually, the EV energy consumption, *E*, can be obtained as follows

$$E = P_{\rm batt} t \tag{24}$$

where, *t* is the travel time. In order to ensure the safe operation of the battery, SoC, which is defined as follows, is taken into consideration as a constraint in the routing algorithm [28], [34]

$$SoC = 100\left(1 - \frac{1}{Q_{\rm batt}} \int_0^t \frac{i_{\rm batt}(t)}{3600} dt\right) \tag{25}$$

where, $Q_{\rm batt}$ is the battery maximum capacity. The maximum and minimum values of SoC are 100% and 0%, which refer to fully charged and discharged states of the battery, respectively. If SoC is more than its maximum limit, the surplus energy recuperated from braking will not be recovered. If SoC is less than its minimum value, the battery will not be capable of supplying the required energy to the vehicle. Typically, a more conservative value is considered as the minimum SoC value [34]. Therefore, when an efficient route is selected for an EV, it must be ensured that SoC will remain within a proper range:

$$SoC_{\min} \leq SoC \leq SoC_{\max} \tag{26}$$

V. Application of Data Mining in the Proposed Routing Algorithm

A. Data Gathering

As aforementioned, the backbone of the proposed method is based on mining historical driving data. Gathering these data has become possible thanks to the recent advances in communication networks and vehicles equipped with global positioning system (GPS). During a travel, GPS can record speed, position and altitude. In addition, corresponding instantaneous energy consumption of EV and SoC can be recorded. Then, at the end of the travel, these data besides time of the travel and the EV code are communicated to the database center. In the database center, in according to the travel time, the traffic level, obtained from a public traffic information system (TIS), as well as temperature during the travel are gathered. Finally, these sets of data are stored in the database center and form historical driving data for a segment, which can be used for other drivers with similar driving conditions and vehicle characteristics and intend to pass through the same segments in the future.

B. Data Mining for EV Routing

In order to use historical driving data and find a desired and feasible route and speed profile for a goal driver, there must be a strong analogy between the goal driver's and historical drivers' driving condition and the vehicle characteristics. To meet this requirement, data mining techniques are employed.

Data mining is search for useful information from a huge volume of raw data. Since formation of data mining techniques, numerous methods such as classification, association, pattern matching, data visualization, evolution, generalization, and characterization have been introduced [35]. Classification, which can be either unsupervised or supervised, is one of the important aspects of data mining. In unsupervised classification, also known as clustering, no labeled data are partitioned into the clusters. In the proposed routing algorithm, the clustering methods are employed to cluster the stored historical driving data in the database center based on their attributes. The clustering is carried out offline and the results are stored in the center (see Fig. 2).

In supervised classification, new input data vectors are assigned to finite sets of discrete classes. Classification algorithms mainly work based on proximity of attributes. To this end, classification must be applied to determine the class of the goal driver among the classified historical driving data. Classification ensures that a cluster is selected which attributes of its samples have the most analogy to those of the goal driver. In this paper, K-means and Naïve Bayes, which are two popular data mining methods, are employed for clustering and classification of data, respectively, and are explained in more details in the following subsections.

1) K-Means Clustering: K-means is a simple and effective iterative distance-based clustering method [36]. In this method, the desired number of clusters (parameter *K*) should be specified in advance. As the first step, *K* points are chosen randomly as initial cluster centers. Then, all the instances in the dataset are assigned to their closest cluster center according to the distance measured by an appropriate metric. In this paper, Euclidean distance, which is defined in (27), is employed to measure the distance between two points $\mathbf{x} = (x_1, x_2, \ldots, x_D)$ and $\mathbf{y} = (y_1, y_2, \ldots, y_D)$

$$dist(\boldsymbol{x}, \boldsymbol{y}) = \sqrt{\sum\nolimits_{i=1}^{D} (x_i - y_i)^2} \tag{27}$$

Here, *D* is the number of dimensions (attributes) of each point.

In the next step, the mean of all points in each cluster is calculated and is taken as the new centroid point in that cluster. After determining new cluster centers for all the clusters, this iterative process continues until the cluster centers remain unchanged in consecutive rounds.

The performance of K-means is evaluated by the following function

$$E = \sum_{i=1}^{K} \sum_{\mathrm{x}_i \in C_i} |dis(\boldsymbol{x}_i, c_i)|^2 \tag{28}$$

where C_i is *i*-th cluster with center c_i, and $\boldsymbol{x}_i$ is set of points in that cluster. As it can be concluded from (28), K-means algorithm tries to minimize the total squared distance from points to their cluster centers.

2) Naïve Bayes Classification: Naïve Bayes is a simple probabilistic classifier based on Bayes theorem by assumption of strong (naïve) conditionally independence [37]. Let *C* shows class variables used in classification, E_i denotes conditional *i*-th attribute used for classification, and $0 \leq P(C|E_1, \ldots, E_{\mathrm{n}}) \leq 1$ be conditional probability of class *C* given that the evidence $E_1, \ldots, E_n$ have occurred. The probability model for a Naïve Bayes classifier can be written as

$$P(C|E_1, ..., E_n) = \frac{P(C) \times P(E_1, ..., E_n|C)}{P(E_1, ..., E_n)} \tag{29}$$

Since the attributes are assumed to be independent, (29) can be rewritten as

$$P(C|E_1, ..., E_n) = \frac{P(C) \times P(E_1|C) \times ... \times P(E_n|C)}{P(E_1, ..., E_n)} \tag{30}$$

From classification point of view, (29) and (30) are called the likelihood functions when they are expressed as a function of *C* given *E*. For class variables $C_1, \ldots, C_m$, evidence can be classified into *m* values of likelihood. Then, the evidence is assigned to the class with maximum likelihood. Comparing (30) with likelihood function, $P(E_1, \ldots, E_n)$ can be dropped from

(30) as it is constant. Therefore, the likelihood function can be written as follows

$$\text{Likelihood }(C_i) = P(C_i) \times P(E_1|C_i) \times ... \times P(E_n|C_i) \tag{31}$$

The above equation is more practical as it does not need a very large training set. The reason is that the evidence was partitioned into multiple attributes by independence assumption. Also, class conditional densities can be calculated separately for each attribute and a multi-dimensional task is broken down to multiple one-dimensional tasks.

3) Driving and Vehicle Attributes Selection: When two drivers share the similar driving and vehicle attributes, their driving conditions can be considered analogous. Consequently, they can be considered in the same class. The following vehicle features and driving conditions that significantly affect the EV energy consumption and speed are chosen as attributes for classification.

1) *Mass of vehicle and cargo*: It is clear from (1)–(5) that the vehicle mass, rolling coefficient, vehicle frontal area and aerodynamic drag coefficient are features of each individual vehicle that might affect its energy consumption. Among these features, the vehicle mass has the most impact on energy consumption, and therefore, is considered as the first attribute for classification.
2) *Temperature*: Among EV's auxiliary loads, HVAC consumes bulk of the power. Since its energy consumption is temperature-dependent, temperature is considered as the second attribute.
3) *Time of travel*: Headlights, which are considered as auxiliary loads, are typically on at night. Hence, day or night is selected as the third attribute. Another reason for this selection is that the speed profiles recorded during day may not be repeated at night as drivers tend to drive more carefully at dark.
4) *Traffic level*: Traffic level has the most influence on the vehicles speed profiles. Since traffic patterns tend to be repetitive [41], it is likely that the goal driver can follow the desired speed profile obtained from historical speed profiles. By considering the traffic level as the fourth attribute, and assuming that the real-time traffic data are available, the data mining approach will ensure that the selected historical driving data for analysis and the real-time data have matching traffic levels.
5) *Propulsion motor power*: Motor power is selected as another important attribute since the algorithm might dictate a speed profile that requires rapid accelerations and decelerations. However, such transients could not be followed due to the rated power of the propulsion motor.

It is noteworthy to mention that although five attributes are considered for classification, more number of attributes, such as age of the driver and weather conditions, can be considered, as well.

VI. Case Study

In this section, the steps of the proposed algorithm are explained through a sample case study and the obtained results are presented. As already mentioned, historical driving data are obtained from the Warrigal dataset [38]. The Warrigal project, which is available online, provides real vehicle state information for three years driving period with resolution of one second. The vehicle state information includes speed, altitude, and position of the driver (easting and northing). A typical map of Warrigal data set is shown in Fig. 7.

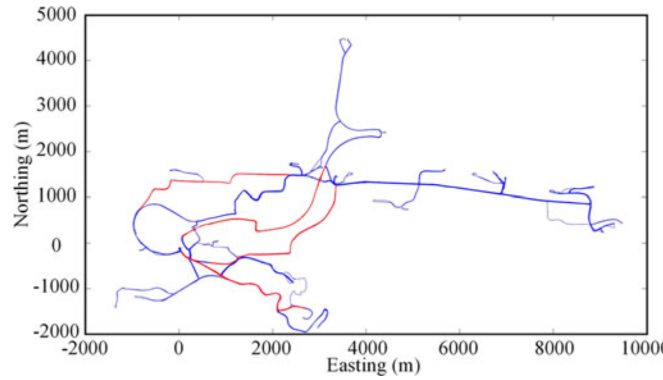

Fig. 7. A typical map from Warrigal dataset [38].

TABLE I
Parameters of the Selected EV and NCR18650B Battery Cell

Parameters	Values	Parameters	Values
A_f	2.341 [m^2]	$\eta_{\rm dc}$	0.95
r_w	0.353 [m]	E_0	3.0043 [V]
G	9.73	R	0.049863 [Ω]
C_d	0.24	K	0.00492 [Ω]
$V_{\rm dc}$	420 [V]	Q	2.9 [Ah]
$\eta_{\rm TS}$	0.95	A	1.1358 [V]
η_m	0.9	B	0.34992 [(Ah)$^{-1}$]
$\eta_{\rm inv}$	0.9	N_s, N_p	74, 96

Since energy consumption is not available in the Warrigal dataset, energy consumption corresponding to each speed profile in the dataset is calculated from the presented EV model in Section IV. The battery parameters, obtained from Li-Ion Panasonic NCR18650B battery cell datasheet, and required information for calculating the acting forces on the vehicle are listed in Table I. The vehicle parameters are mainly adopted from Tesla Model S P85. For other vehicle models, manufacturers can provide such parameters. If parameters are not available, they can be estimated from those of the other vehicles in the same class.

In this study, level of service (LOS) is employed for expressing the traffic level. Six levels of service (A to F) are defined in the Highway Capacity Manual (HCM) as criteria for evaluating roadway performance [23]. There are numerous LOS prediction methods that can be employed for determining the traffic level at each segment. Since the traffic level and four remaining attributes, i.e., mass, temperature, time of the travel and propulsion motor power, are not available in the Warrigal dataset, they are generated randomly and associated with the speed profiles. Temperature, mass and propulsion motor power are generated based on Beta distribution to achieve asymmetrical distribution of data. Uniform distribution is employed for generating time

TABLE II
RANGE OF GENERATED ATTRIBUTES

Attribute	Range
Temperature [°C]	[−10, 40]
Weight [kg]	[500, 3855]
Electric Motor Power [kW]	[15, 600]
Time	{1, 2}
Traffic	{A, B, C, D, E, F}

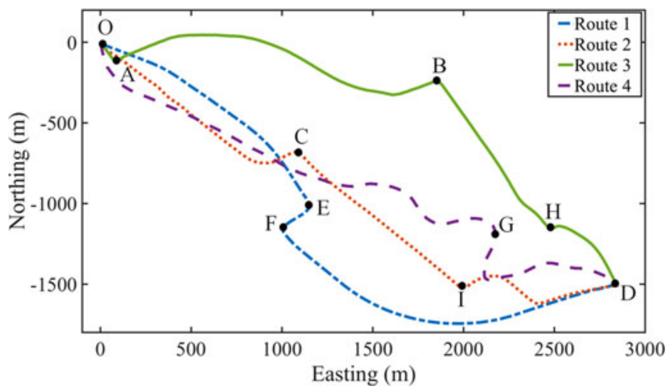

Fig. 8. Candidate efficient routes.

TABLE III
ROUTE CONDITION AND LOS PREDICTION OF SEGMENTS PRIOR TO RUNNING THE ALGORITHM

Route Number	Length [m]	Segment Number	LOS Prediction
Route 1	3868	Segment 1	C
		Segment 2	D
		Segment 3	B
Route 2	3574	Segment 1	D
		Segment 2	E
		Segment 3	D
Route 3	3694	Segment 1	C
		Segment 2	B
		Segment 3	B
		Segment 4	C
Route 4	3742	Segment 1	E
		Segment 2	E

TABLE IV
10 FIRST SAMPLES OF 57 SAMPLES IN CLUSTER 797

Sample No.	Temp. [°C]	Weight [kg]	EM Power [kW]	Time Period	LOS
1	28	2200	370	Night	C
2	28	2200	370	Night	C
3	30	2300	370	Night	C
4	28	2400	370	Night	C
5	29	2400	370	Night	C
6	24	2100	410	Night	C
7	25	2100	410	Night	C
8	27	2100	390	Night	C
9	30	2100	400	Night	C
10	31	2100	400	Night	C
Average	27.7	2282	409.4	Night	C

TABLE V
MINIMUM ENERGY CONSUMPTION AND TRAVEL TIME FOR SEGMENTS OF CANDIDATE ROUTES

Route Number	Segment Code	Minimum Energy Consumption		Minimum Travel Time	
		Energy Cons. [wh]	Travel Time [s]	Energy Cons. [wh]	Travel Time [s]
Route 1	OE	297.7	85	362.3	78
	EF	37.6	16	113.4	10
	FD	252.4	105	270.5	93
Route 2	OC	265.7	111	459.6	59
	CI	273.9	105	523.1	54
	ID	254.6	89	428.4	46
Route 3	OA	42.1	7	50.9	7
	AB	425.5	115	596.5	89
	BH	271.1	70	402.6	57
	HD	165.7	32	299.5	23
Route 4	OG	1279.7	251	1386.5	245
	GD	386.8	95	395.6	93

TABLE VI
TIME AND ENERGY EFFICIENT ROUTES BASED ON BEST SPEED PROFILE

	Route No.	Energy Cons. [wh]	Travel Time [s]
Energy Efficient	1	587	201
Time Efficient	2	1201	159

of the day and traffic condition since the range of such data is limited. Table II shows the ranges that are imposed on the randomly generated attributes. Following this procedure, 64000 sets of attributes are generated for each segment.

Afterwards, data mining approaches are employed to cluster the generated historical driving data for each segment. The Waikato Environment for Knowledge Analysis (Weka) is employed for implementation of clustering. Weka is a powerful tool that provides an extensive collection of machine learning and data processing techniques [39]. K-means is employed for clustering each segment's data based on the previously defined five attributes. The number of clusters is chosen to be 1000 to balance out the within-cluster sum of squared errors (28) and the average number of samples per cluster. It is noteworthy to mention that clustering is carried out offline in practice.

As the first step to use the routing service, the goal driver determines points O and D as the origin and destination of travel, respectively. Then, GPS coordinates along with the vehicle code and initial SoC are sent to the database center through communication network. In the database center, the candidate routes are determined based on common shortest-time routing algorithms [25], [26]. Here, it is assumed that the four routes that lead to the shortest travel time are selected. The candidate routes in this case study are distinguished from others with red color in Fig. 7 and depicted separately in Fig. 8. 141, 39, 42 and 142 distinctive speed profiles were available for routes 1 to 4, respectively. Next, based on the available maps in the database center, the number of segments in each candidate route is determined and a code is assigned to each segment. Table III summarizes the information of the four candidate routes, including the route

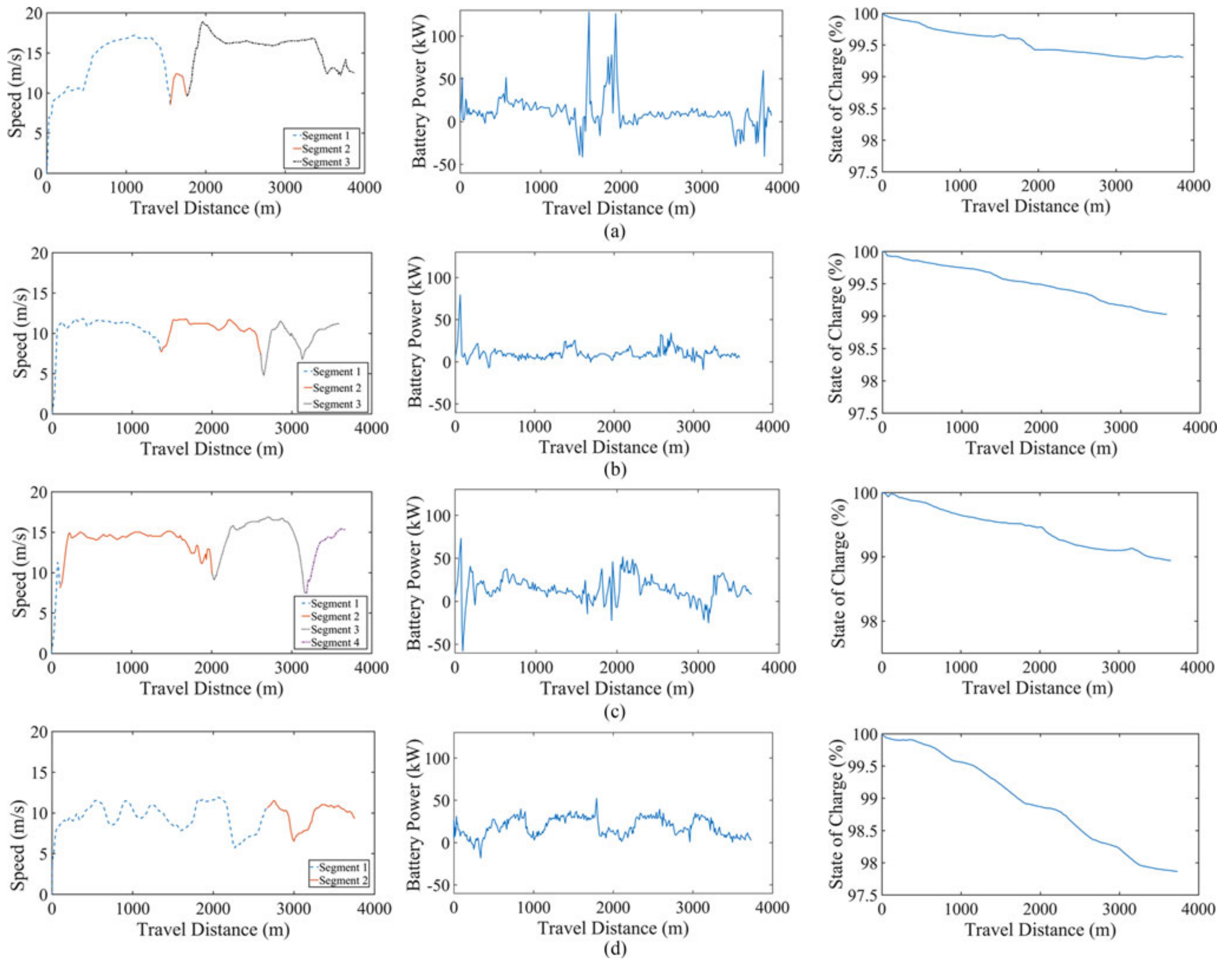

Fig. 9. Speed profile, energy consumption and state of charge (from left to right) for (a) first candidate route, (b) second candidate route, (c) third candidate route, (d) fourth candidate route when energy consumption is considered as the cost function.

length, number of segments in each route, segment codes, and real-time traffic prediction for each segment.

In the next step, the driving and vehicle attributes are classified based on the goal driver's driving conditions and the vehicle characteristics. It is assumed that the vehicle mass is 2170 [kg], the traction motor's power is 350 [kW], travel takes place at night and the air temperature is 28 [$^{\circ}$C]. Classification is carried out through Weka. Training Naïve Bayes by data of the segments shows accuracy of 95%. The classifiers were trained by the 10-fold cross validation method. This method creates 10 partitions of the dataset such that each partition has 90% of the instances as a training set and 10% as an evaluation set. The benefit of this technique is that it uses all the data for building the model, and the results often exhibit significantly less variance than those of simpler techniques such as the holdout method (e.g., 70% training set, 30% testing set). Classifying the first segment's clusters in the first candidate route by using Naïve Bayes algorithm results in selection of cluster number 797, which contains 57 samples. Due to limited number of pages, only attributes of the first 10 samples out of the available 57 samples are listed in Table IV. Also, the average of all 57 samples' attributes in that cluster is provided. By examining the results, one can see that the attributes of the selected cluster are close to those of the goal driver. Therefore, the energy consumption of the goal driver's EV can be estimated with an acceptable accuracy. Following this step, historical driving data of the selected class for each segment can be used to extract the efficient speed profile.

The efficient speed profile results in a minimum cost function. Note that the cost function can be selected as either the consumed energy for traveling a segment, or travel time or a combination of both. After extracting the speed profile, it must be verified whether it meets the SoC constraints as expressed in (26). The minimum cost function for each route can be then calculated by summing up the obtained minimum cost functions for each segment.

Table V lists the consumed energy and travel time through each segment when the desired speed profile is selected based on energy consumption and travel time minimization. The time and energy efficient routes, given in Table VI, result in the

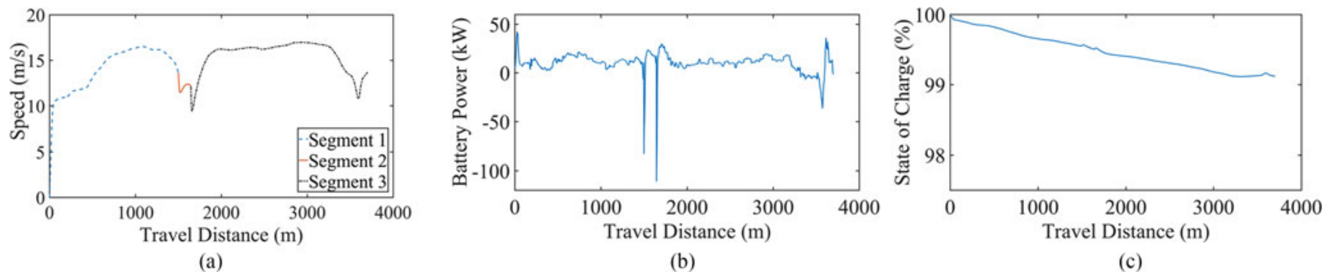

Fig. 10. (a) Speed profile, (b) energy consumption profile, (c) SoC of efficient route (route 1) when the average of speed profiles is used to find the most energy efficient route.

TABLE VII
TIME AND ENERGY EFFICIENT ROUTES BASED ON AVERAGE SPEED PROFILES

	Route No.	Energy Cons. [wh]	Travel Time [s]
Energy Efficient	1	761	231
Time Efficient	3	1145	204

lowest values of cost functions (time and energy consumption) among the candidate routes. According to Table VI, out of the four candidate routes, the first one leads to maximum energy savings and the second one leads to minimum travel time. It is obvious that the shortest-time route is not necessarily the route with minimum energy consumption. By examining the results, one can see that the goal driver can save 51.1% battery energy at the expense of spending 26.4% longer time driving if he/she takes the route with minimum energy consumption.

Fig. 9 illustrates speed profile, energy consumption and SoC for all the four candidate routes, when energy consumption is considered as the cost function. The speed profile for a route is formed by combining the efficient speed profiles obtained for each segment. It is assumed that initial SoC is 100%, or in other words the battery is fully charged at the beginning of the trip. Since the lengths of the routs are short, SoC variations are not very significant. Examining the results verify the fact that the routes with minimum accelerations and decelerations lead to more energy savings and vice versa. For example, the fourth candidate route, which demands several decelerations and accelerations, shows maximum energy consumption among the candidate routes.

For the second approach, the average of historical speed profiles through each segment is selected as the desired speed profile and the obtained results are shown in Fig. 10. In this scenario, route 1 is selected again when energy consumption is considered as the cost function. However, route 3 is selected as the shortest-time route. Table VII lists the travel time and energy consumption with both cost functions. Comparing these values with those listed in Table VI, it is clear that the travel time and energy consumption through time and energy efficient routes are higher when the average speed profile is followed.

Although traffic patterns tend to be repetitive, there might be unforeseen circumstances where the goal driver cannot follow the desired speed profile accurately. In order to demonstrate the effect of unwanted speed deviations on the EV energy consumption, a test is carried out where random accelerations and decelerations are applied to the energy efficient speed profile. Fig. 11 depicts this scenario. Two instances of unwanted accelerations/decelerations, specified by circles in the figure, are imposed on the energy efficient speed profile. Under this condition, SoC changes slightly compared to the ideal case in Fig. 9 (a). Also, energy consumption shows a 1.8% increase and is equal to 598 [wh]. This test confirms that with slight unwanted deviations from the desired speed profile, the predicted energy consumption would not be affected significantly.

Fig. 12 depicts speed profile, energy consumption and SoC on the second candidate route, which is selected as the efficient route when travel time is considered as the cost function (see Table VI). It must be clarified that the obtained results are different from those obtained at the first stage of the algorithm where candidate routes are determined. That is because at the first stage, the shortest-time routes are determined based on the average time required for travelling the segments, while here, travel time is determined assuming that the driver will follow the efficient speed profile.

As a comparison, the routing algorithm proposed in [9] is employed for the same case study and the obtained results are summarized in Table VIII. In [9], energy consumption is estimated by considering the speed and slope angle of each segment constant. Also, the impact of auxiliary loads in the EV energy consumption is neglected. By comparing the results provided in Tables V and VIII, it can be concluded that although, similar to the proposed routing algorithm, the algorithm proposed in [9] selects route 1 as the energy efficient route, but route 3, rather than route 2, is selected as the time efficient route. Furthermore, significant disparities between the estimated energy consumption (on some segments) by the two algorithms can be noticed. The unrealistic assumption of constant speed and slope through each segment as well as ignoring the effect of auxiliary loads on the energy consumption lead to inaccurate selection of the time and/or energy efficient route.

It should be noted that by continuous recording and storing of data, the proposed routing algorithm will yield results closer to the best possible solution, i.e., global optima. Also, vehicles of future will be equipped with adaptive cruise controllers (proposed in [40]), in which the speed of the vehicle is optimally adjusted in real time based on onboard sensors. The collected data from such vehicles will reflect the roadway and environmental conditions more accurately. As a result, the proposed

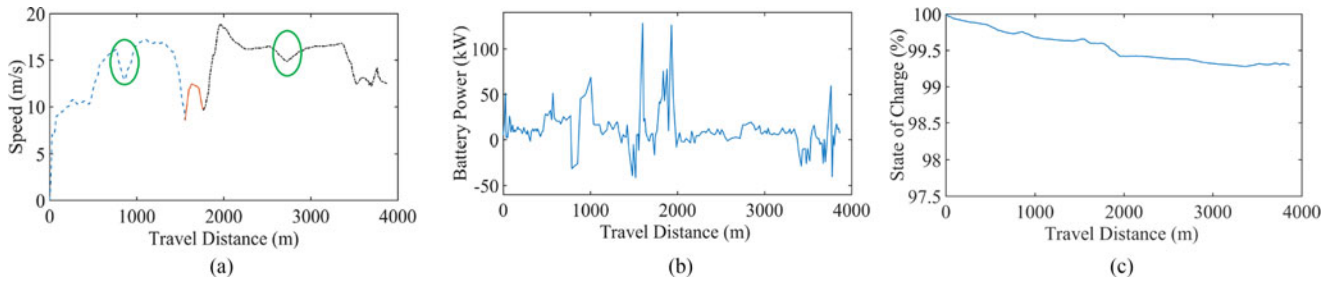

Fig. 11. (a) Speed profile, (b) energy consumption profile, (c) SoC of efficient route (route 1) under unwanted speed deviations.

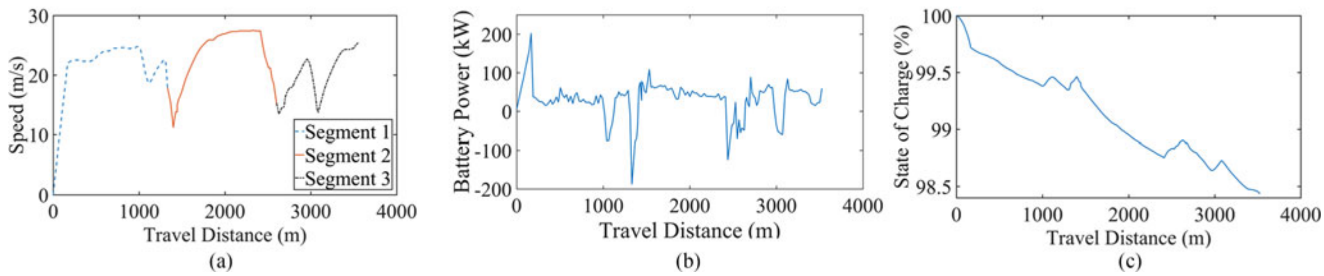

Fig. 12. (a) Speed profile, (b) energy consumption profile, (c) SoC for second candidate route when travel time is considered as the cost function.

TABLE VIII
ENERGY CONSUMPTION AND TRAVEL TIME FOR SEGMENTS OF THE CANDIDATE ROUTES OBTAINED BASED ON THE METHOD IN [9]

Route Number	Segment Number (Segment Code)	Energy Consumption [wh]	Travel Time [s]
Route 1	Seg.1 (OE)	341	75
	Seg. 2 (EF)	91	13
	Seg. 3 (FD)	267	89
Route 2	Seg. 1 (OC)	251	55
	Seg. 2 (CI)	339	49
	Seg. 3 (ID)	278	42
Route 3	Seg. 1 (OA)	−30	6
	Seg. 2 (AB)	540	74
	Seg. 3 (BH)	342	46
	Seg. 4 (HD)	85	18
Route 4	Seg. 1 (OG)	1287	211
	Seg. 2 (GD)	402	86

algorithm can yield more realistic or even more efficient speed profiles based on the data gathered from such vehicles.

VII. CONCLUSION AND FUTURE WORK

An algorithm for EV efficient routing that results in either minimum energy consumption or minimum travel time is proposed. The algorithm employs data mining techniques to obtain an efficient route based on historical driving data. It is concluded that the shortest-time route is not necessarily the energy efficient path and different factors such as roadway conditions and driving style have significant effect on the energy consumption. Unlike the existing routing techniques in which the link speed and slope are considered constant, an efficient speed profile is considered in the proposed routing algorithm. Another significant advantage of the proposed method is that since roadway conditions and traffic level are inherently embedded in the historical driving data, the obtained results from the proposed algorithm reflect those conditions. In addition, by continuous recording of up-to-date data, the most recent changes in the driving conditions, such as speed limits or traffic level, will be automatically reflected in the gathered data and there will be no need to update those conditions in the routing algorithm.

The following topics are proposed for future studies

1) The proposed algorithm can be employed for range estimation of EVs.
2) Different objectives, such as necessity of passing through a charging station, can be considered in the efficient routing problem.
3) The proposed algorithm can be extended to interrupted roadways, where effect of signalized intersections are considered.

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