Energy consumption estimation for electric vehicles usning routing API data

Saad Alateef[1]

School of Computing
Newcastle University
Newcastle upon Tyne, UK

Nigel Thomas[2]

School of Computing
Newcastle University
Newcastle upon Tyne, UK

Abstract

Electric vehicle (EV) range anxiety is an influential factor in electric vehicle's low penetration into the transportation system. There have been several developments on range estimation for electric vehicles, however, the studies which focus on determining the remaining range based on the real-time publicly available data remain low. The majority of the current methods being employed consider limited data collection and do not consider the most substantial factors that directly impact energy consumption. This paper introduces a velocity model based on route information for the range estimation of electric vehicles. It uses publicly available data sets obtained from several map services APIs and incorporates this data in the range estimation algorithm. Three map services APIs were used to collect the data for an extended period, and then we analysed this data to extract the most representative data to generate the velocity profiles. The paper uses MATLAB code and python libraries to process the representative data and apply the velocity model. Moreover, we have integrated it into an electric vehicle model, including the battery, to estimate the power demand for each trip and the remaining driving range. We observed that producing realistic driving cycles using public data is possible; furthermore, it simulates the driving patterns and satisfies the constraints of the vehicle.

Keywords: Routing API, Electric vehicles, SOC estimation

1 Introduction

Electrifying transportation is one of the main targets for the transportation sector to reduce greenhouse emissions in most countries [1]. However, Internal Combustion Engines (ICEs) are entirely dependent upon fossil fuels and still the primary propulsion system in road transport globally. The increase in the dependency on oil is considered significant as a result [2]. Therefore, there is an essential need to overcome this issue to increase the sustainability of the transportation system and address the environmental issues. The demand for electric vehicles has been increasing recently in the transportation markets, and it is expected to continue to replace traditional vehicles in the next few decades. EVs are an intelligent solution for the planet and will reduce gas emission significantly [3]. However, range anxiety is one of the main challenges that face electrifying transportation, and it affects the adoption of electric vehicles.

In addition to the enormous advantage of reducing the levels of pollution EVs have, this invention has some other benefits over conventional vehicles. These benefits include energy recovery when the battery restores some of the energy due to braking, and the noise-freeness [4]. Regenerative braking is a crucial characteristic

[1] Email: s.alateef1@ncl.ac.uk
[2] Email: nigel.thomas@ncl.ac.uk

of EV when the generator returns the energy to the battery system due to braking. According to previous studies, this feature is practical, especially in city driving and the daily commute. However, it is less effective in motorway journeys, and long journeys [5]. Conventional vehicles consume more energy in city driving because of the heat loss due to braking in contrast with EVs [3].

This paper aims to develop a velocity model using the publicly available routing data on specific routes. It attempts to construct the speed profile for a specific journey between origin and destination using the map API. After generating the potential realistic driving profile, we used a generic EV model to generate the potential power demand for the trip. Hence we apply the state of charge estimation method to analyse the impact of the route and traffic on the battery efficiency. This research concentrates essentially on developing a data collection process using multiple maps service API. Many drivers rely on the GPS data provided by map services to navigate to their destinations [6]. This paper uses the data collected from the drivers using the map API. The first step of this paper involves exploring the routing information and using it to estimate the energy consumption and improve the battery-powered vehicles' efficiency. This research explores the data of three different map information providers through their API. Google Maps API [7], HERE Maps API [8] and TomTom Maps API [9] are the primary data sources in this research.

The amount of data collected from vehicles and drivers can significantly improve the range of electric vehicles [10]. The battery management system (BMS) installed in electric vehicles senses the battery state of charge and predicts the remaining range based on the battery status and some other data installed on the system such as the vehicles' specifications data. However, these data-sets do not consider the route information ahead. Therefore, it uses the range values for its estimation. The proper use of the available data can improve the driving range prediction and improve the energy consumption estimation.
In this paper we construct near to real-time velocity profiles to allow us to generate power profiles and estimate the power consumption before performing the journey.

1.1 Energy consumption and driving cycles

Energy consumption in transportation systems has been a significant research and development topic recently [11]. Previous work focused on how the driving behaviours affect the fuel consumption in internal combustion engine (ICEs) vehicles [12]. In recent years, further studies have been conducted on the usage and consumption of EVs [13]. These studies are characterised based on their methodology, and purpose [14]. In addition, some researchers focus on the energy models of electric vehicles to improve the EV design [15], exploring the influential factors on power consumption [16] and the influence of the driving patterns on the energy consumption and the remaining driving range [17].
Whilst, there are many studies in the literature to improve the energy consumption of electric vehicles; there is less research conducted on energy consumption based on the real-time velocity profile prediction. These profiles are known as driving cycles for vehicles and generally defined as a series of points representing speed versus time. The driving cycle is usually performed as a physical journey on a vehicle for various purposes and based on various criteria [18].
Driving cycles developed in recent decades are used as a standard tool for estimating fuel consumption and measuring the levels of air pollution produced by the transportation system. Many existing standard industrial driving cycles such as NYCC, UDDS, and HWFET, have been used in some studies [19,20]. These driving cycles are used as velocity profiles for validating the EV and battery models response. The current driving cycles performed in unknown conditions and do not represent the real-time driving conditions. Some existing studies developed methods to predict the driving profile [21,22], and each method relies on the nature of the data used to develop this prediction method [23]. The map service API can help up to some extent to develop and improve the real-time driving cycle construction methods. The API provides a wide range of route information for any geographical location on the map and also considers the traffic situation. Even though the API providers restrict developers from some features for commercial and competition reasons, it is still possible to extract some valuable data to help to predict the journey and the velocity characteristics to improve the range and energy estimation for electric vehicles. This approach makes it more convenient than performing the physical journey considering many arrangements and set-ups such as a vehicle, driver and some equipment making it a costly task [24].

2 Data collection process and analysis

2.1 Traffic data exploration

This section illustrates the process and the purpose of exploring the traffic data. In addition, the data collection process and the challenges faced are also presented.

(i) Route Selection:
The main objective of collecting the data from the map service providers is to create a generic script that gathers time-specific traffic data between two different Geo locations following a specific route. We have specified the origin and destination on the map for two different routes that have different road structures. These routes were sliced into multiple chunks so that we can collect more accurate data for each chunk. Collecting the data for smaller segments is to separate the parts of the route that have possibilities of speed reduction from more continuous high-speed such as motorways.

(ii) Data Analysis:
The data provided from the APIs are “duration”, “distance” and “segments”. Each segment profile includes duration and distance. Since the distance and the time are known, we can calculate the average speed for each segment and therefore, for the entire route. The plots for these raw collected data gives us an idea of what the speed profile, as it presents the average speed for each segment of the route.

(iii) Data Manipulation:
Since the data obtained from the APIs are only average speed based on the duration in traffic and distance of the segment, it provides a constant speed for each chunk of the road. Therefore, we introduce some changes to those average speeds to reflect more realistic driving patterns. Therefore, it can represent the velocity of the vehicle in each segment without altering the mean value of the speed provided from the API data

2.2 Data collection

(i) Data collection methodology.
- Extracting the data from the API provider.
- Collecting data from the API response.
- Scheduling the collection process for specific times.
- Loading the data into a CSV format.

(ii) Source of traffic data.
- Google Maps API
  The API products provided from Google Maps were used as follows:
  · Distance Matrix API: This API allows us to get the travel distance and time for the entire route and each identified segment. In addition, it allows us to obtain the estimated duration within the current traffic.
  · Directions API: Allows introducing the way-points which helps force the API to follow the route we specify; it is also responsible for the mode of transportation, which is ”Car” in our case.
- TomTom Maps API
  The API products provided from TomTom were used as follows:
  · Traffic Flow API : This allows developers to request the travel time from the origin and destination with respect to the real-time traffic.
  · Maps API: This product gives an access to the API data every time we make a request.
  · Routing API : This API gives highly detailed information about the route, with respect to directions and travel mode.
- HERE Maps API
  The API products provided from HERE Maps were used as follows:
  · Routing API: This product informs the estimated arrival time between the origin and destination.
  · Traffic API: This API is responsible for reporting the traffic flow, its consequences and the incidents information.
  · Way-points sequence API: This allows us to specify the way-points on the route to divide it to the segments we require.

(iii) Extracting the time and speed data
- The data of the time taken during current traffic and the average speed calculated are added into separate files for each journey. These files are formatted in two columns that show the time in seconds for the whole journey versus the average speed at each second. These files are then processed to generate possible velocity profiles.

In Table 1, the main features of the used map services API are illustrated.

	Google Map API	Here Map API	TomTom Map API
Free Transactions	40,000 requests per month, 1333 request per day.	250,000 requests per month. 8333 per day.	2500 request per day.
Pricing	$5 for requests from 0 to 100,000.	$1 per 1000 requests.	$0.5 per 1000 requests.
Technology used	Direction and Distance Matrix APIs are being called from python script. Response is in JSON format.	Routing API is being used from python script. Response is in JSON format.	Routing API is being used from python script. Response is in JSON format.
Way-points limit	23 Way-points for each request	50 Way-points for each request.	No limit in way-points but below 128 is recommended in each request.

Table 1
API features

The data was collected at multiple time-slots for each API. These slots were at 8:15am, 12:00pm, 16:45pm and 12:00am. This time selection was done to evaluate and analyse the differences between the peak traffic hours and when it is quiet.

During each slot, the data is requested for an hour, and then loaded the data into CSV files in several rows. The number of rows are dependent upon how many intermediate points were introduced. The data consists of many columns starting from the date when the data was collected, until the average speed that was calculated using the distance and the duration in traffic. Each row is a repetition of the same process during the specific time we selected. Figure 1 illustrates a step by-step-process of collecting the data through the APIs.

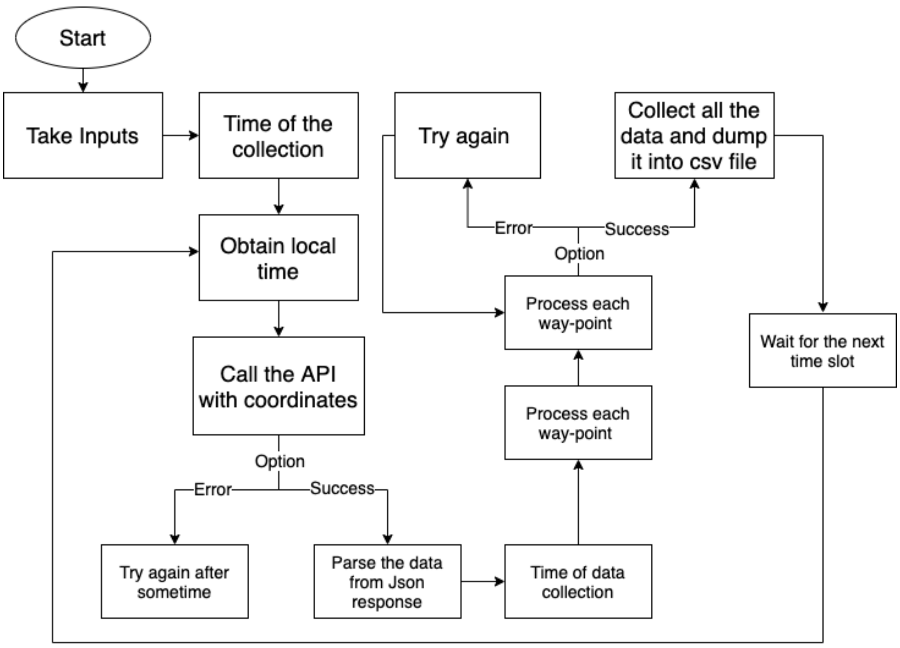

Fig. 1. Data Collection Process

3 Route based driving cycle construction

This section explains how the acceleration and deceleration is applied to the average speed data then add the noise function to introduce some kind of variations to the speed profile wherever it is constant. In addition it

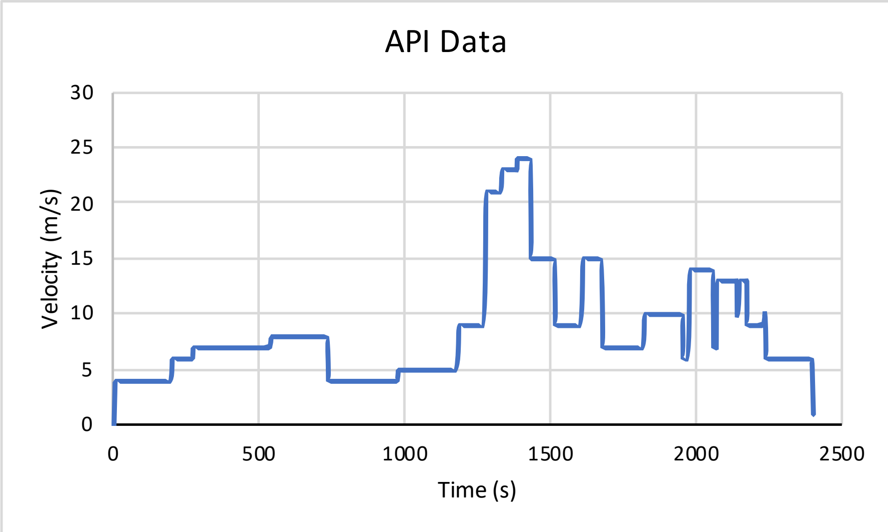

Fig. 2. Mean velocity obtained from HERE Maps API

illustrates the method used to smooth the velocity curves.

3.1 Applying acceleration and deceleration between route segments

To smooth the transition of velocity between segments, we applied the acceleration and deceleration rate to the beginning and ending intervals. Based on Nissan leaf's 2019 [25] acceleration rate for 0-100 km/h, we determine the maximum acceleration on the car. We consider that the acceleration and deceleration rates the same.

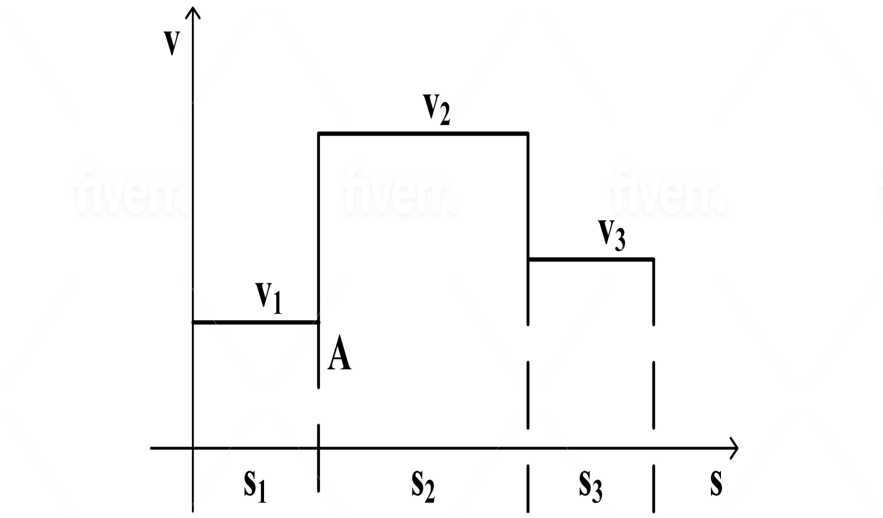

Fig. 3. The initial driving cycle before the speed transition between segments

Using the data retrieved from the API, we obtain the initial driving cycle as shown in Figure 3. It is characterised by sharp edges, corresponding with unrealistic significant speed changes. In addition it does not take into account the technical constraints imposed by the vehicle and the road characteristics. Therefore, the final driving cycle needs to be developed realistically before performing the energy consumption estimation.

The process of developing the driving cycle is implemented in iterative manner. In Figure 4, the driving cycle shows three different segments which constant speeds. The velocity on the first segment is assumed to be at speed V_1, and since the recorded velocity on the second segment is higher than the vehicle's velocity on the second segment, the vehicle needs to accelerate gradually after exceeding point A. The determination of the acceleration is based on the speed difference between V_1 and V_2 using the following equation:

$$a = \begin{cases} 3.5, & v_2 - v_1 \geq 10\frac{km}{h} \\ \frac{1}{2}(v_2 - v_1), & v_2 - v_1 < 10\frac{km}{h} \end{cases} \tag{1}$$

After determining the acceleration, The time Δt needed for the vehicle to accelerate from the velocity in the first segment V_1 to the following velocity V_2 can be calculated as:

$$\Delta t = \frac{v_2 - v_1}{a} \tag{2}$$

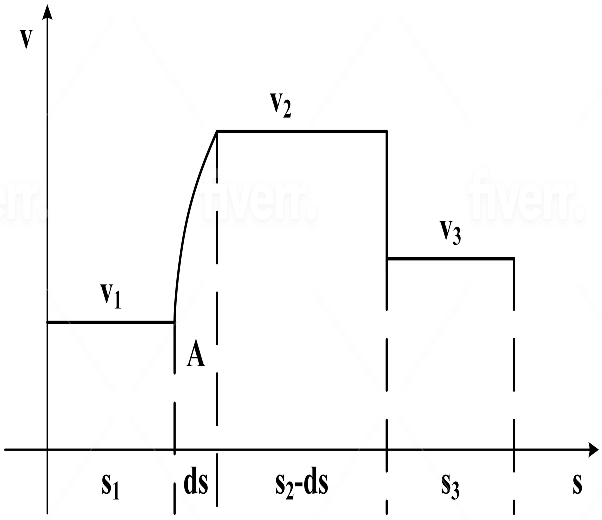

Fig. 4. The gradual acceleration added to the driving cycle

Calculating the distance Δs the vehicle needs during the accelerating process leads to the division of the following segment into separated segments as shown in Figure 5

$$\Delta s = v_1 \Delta t + \frac{a \Delta t^2}{2} \tag{3}$$

The first segment has the length ds where the vehicle acceleration is applied until it reaches the speed V_2. The second segment has the length S_2 - ds when the vehicle's velocity is constant and equals V_2. The API data speed data are often imperfect and inconsistent, it deviates from the real life conditions and constraints. Therefore, the acceleration between velocities are not always feasible, in other words, for the above analysed case of the acceleration from V_1 to V_2, sometimes the distance that the vehicle needs to accelerate is longer than the length of the following segment itself. To overcome this issue, the acceleration V_2 will not take place, moreover, we reduce the speed on the following segment by small step Δ, and repeat the process where the speed on the next segment is V_2 - Δ. This whole process is repeated until it satisfies the feasibility yielding the final driving cycle as shown in Figure 5.

3.2 Adding noise function

To mimic a real driving cycle, we add noise to the intervals in which the speed is constant. The noise is generated as uniformly distributed random numbers in the interval [a, b]. Considering that small variations in speed are accepted, a and b are defined as functions of the maximum and minimum speeds of an interval i.

$$a = -5 \times \frac{1}{minimum(v_i)} \quad \text{and} \quad b = 5 \times \frac{1}{maximum(v_i)} \tag{4}$$

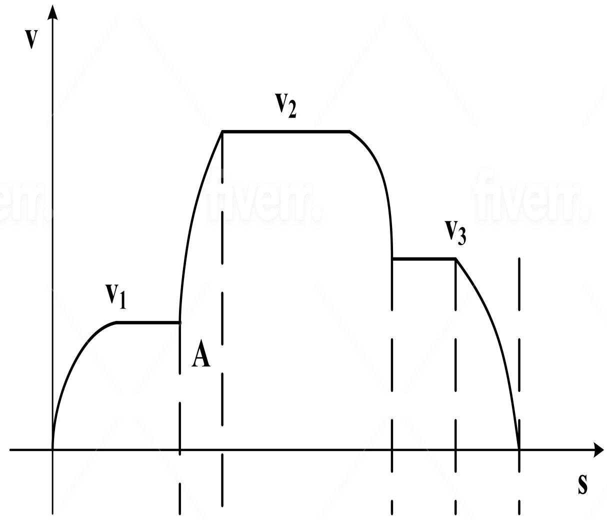

Fig. 5. Final driving cycle after applying the acceleration method

The noise must not interfere in the travelled distance and the average speed in a plateau must remain unchanged. Therefore, the mean of the noise must be zero. To ensure this condition, after the noise n is generated for N samples, it is corrected as follows.

$$n_{i\ corrected} = n_i - \overline{n}, \quad i = 1, 2, \cdots, N \tag{5}$$

3.3 Smoothing the sharp edges

As abrupt variations in speed remain after the acceleration method and noise adding, the last step consists of smoothing the speed curve. We apply the LOESS (locally estimated scatter plot smoothing) method, using 4% of the samples for calculating smoothed values.
LOESS is a method of non-parametric regression that produces a smooth curve by locally fitting polynomial functions. Thus, the fitted values are determined with neighboring subsets of data. LOESS, among other methods, and the percentage of samples are chosen based on a qualitative evaluation of the final driving cycle – the main criteria are the decrease of sharp edges, preservation of noise-induced variations and preservation of the cycle when compared to its pre-processing shape. We determine that the cycle starts and ends at 0 m/s. To ensure a smooth transition, the speed curve is linearly interpolated from zero to the speed value of an arbitrary point at the beginning and ending of the cycle.

After applying the previous methods, the represented driving cycles are generated as shown in the Figure 6. These figures present the velocity profiles for Google Map API after the representative driving cycles are selected for the route. After we constructed driving cycles for each route and API, it is clear that the driving cycle for each API is different at some points on the route and quiet similar at other points along the routes. The generated driving cycles will be used in the next section to develop the power profile for the electric vehicle. Hence, the energy estimation can be performed and the battery dynamics can be captured.

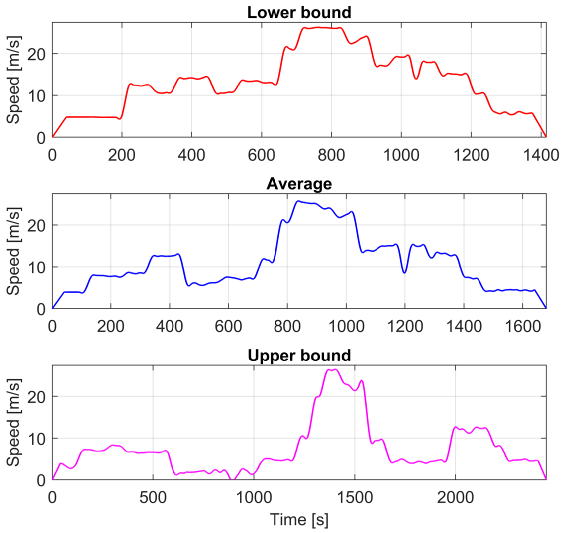

Fig. 6. Google Maps driving cycles for Route 1

4 Generating the power demand using electric vehicle's dynamics

This section consider an electric vehicle model based on existing Nissan leaf to perform the power demand generation and the state of charge estimation based on the data used on this research. With the vehicle speed determined in the driving cycle, we calculate the power consumed to generate the vehicle, or, in case of braking, the power provided back to the battery pack [25].

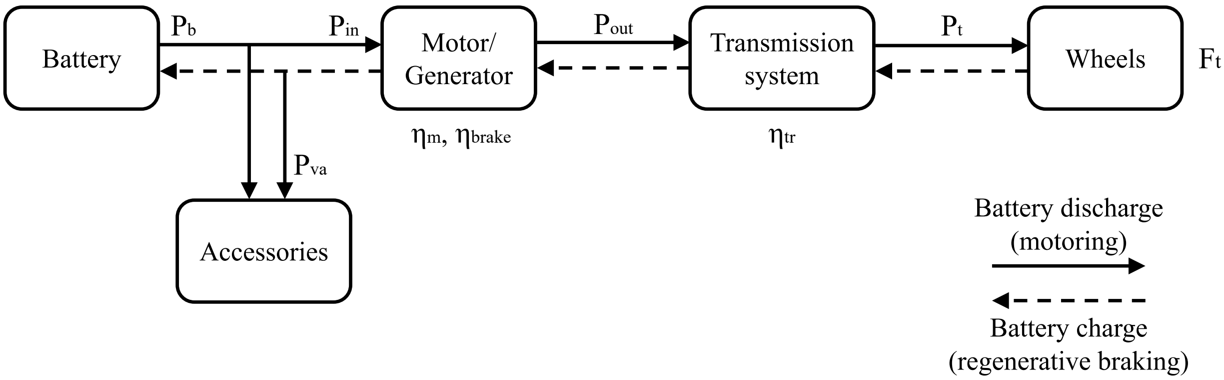

Fig. 7. Electric vehicle power transition diagram

$$F_t(t) = F_r(t) + F_g(t) + F_d(t) + F_a(t) \tag{6}$$

Starting at the wheels, the traction force F_t required for the vehicle's motion is expressed by the sum opposing forces, which is the rolling friction, grade resistance, aerodynamic drag, and acceleration force [26] and [25]. We consider the road slope $\alpha = 0$ for the whole extension of the routes. Even though the road slop data is available from some API map providers, it was not possible to obtain it accurately in this approach, since the way-points were manually selected upon our previous knowledge of the routes, and this makes obtaining the road slope information a complex task and inaccurate due to the uneven route segments length. In addition, we implemented the rolling resistance and the force resisting the tires on the road surface.

4.1 Battery model dynamics and energy consumption estimation

The implementation of the battery model, was considering the Rint model proposed in [27]. This model includes a voltage source V_{oc}, representing the open-circuit voltage, in series with the parallel branch of internal resistance. Any battery model can be implemented in this part of the research to estimate the state of charge based on our power profiles. The current model is less complex and validated in previous studies such as in [27].

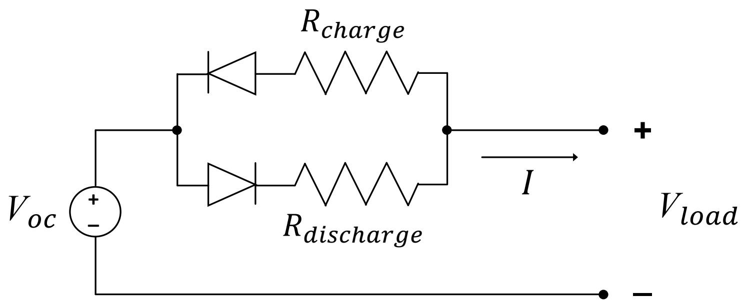

Fig. 8. The equivalent circuit model based on Rint with two resistors in parallel

The current flow in the resisting branch is represented by ideal diodes. When the battery is discharging, the diode in series with the discharging resistance ($R_{discharge}$) conducts the current; contrarily, in case of battery charge, the diode conducting the current is in series with charging resistance (R_{charge}). Given an initial state-of-charge, we start by calculating open-circuit voltage V_{oc} in terms of the SOC, where K, a, b, c and d are constants.

$$
\begin{aligned}
V_{oc}(t) = K - aSOC(t) - b\frac{1}{SOC(t)} \\
+cln(SOC(t)) = dln(1 - SOC(t))
\end{aligned}
$$

The charging or discharging resistance R_s is a function of the SOC and is determined based on look-up tables obtained from [25]. Then, the battery current is calculated by:

$$I(t) = \frac{V_{oc}(t) - \sqrt{V_{oc}(t)^2 - 4R_sP_b(t)}}{2R_s} \tag{7}$$

The current is positive if the battery is discharging, and negative if it is charging. Finally, the SOC is estimated with the coulomb counting method [28], in which the battery current is integrated over time to calculate the transferred charge.

$$SOC(t) = SOC(t_0) - \frac{1}{C_r}\int_{t_0}^{t})I\Delta\tau \tag{8}$$

$$SOC(t) = SOC(t-1) + \frac{I(t)\Delta\tau}{C_r} \tag{9}$$

Where $SOC(t)$ is the current state-of-charge, $SOC(t_0)$ is the initial state-of-charge, C_r is the rated capacity, I is the current flowing in or out of the battery, t_0 is the initial time and t, the current time. Alternatively, the SOC can be expressed in terms of its previously estimated value $SOC(t-1)$ and the current for the time interval of $\Delta\tau = [t-1, t]$.
The equations of V_{oc}, I and SOC are applied iteratively over time to obtain the profiles for a full driving cycle.

5 Results

This section presents the power needed for some journey based on each API and route. It also shows the battery voltage and the state of charge estimation.

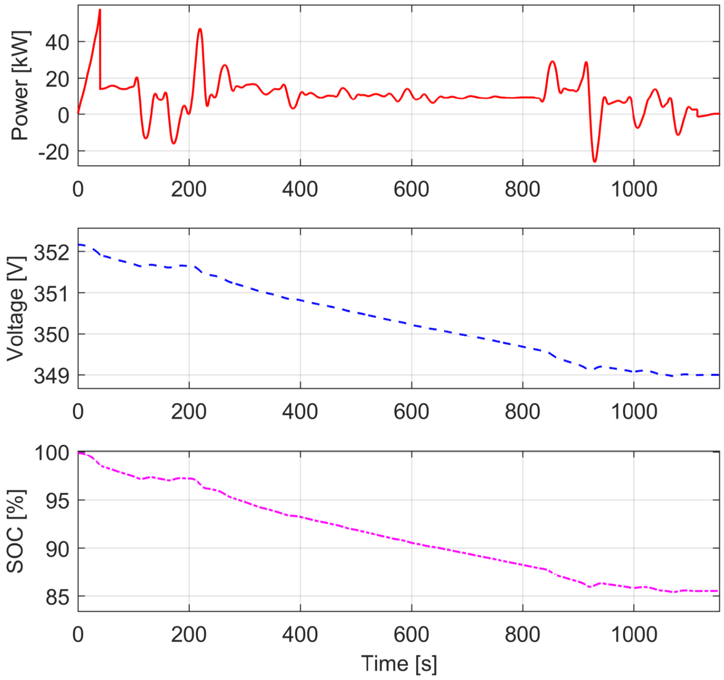

Fig. 9. Lower bound for Google Maps data Route 2

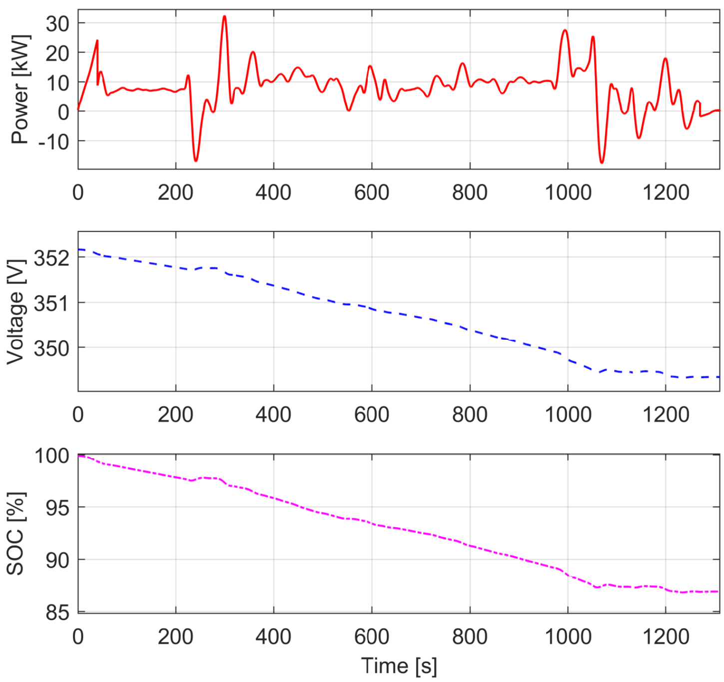

Fig. 10. Lower bound for HERE Maps data Route 2

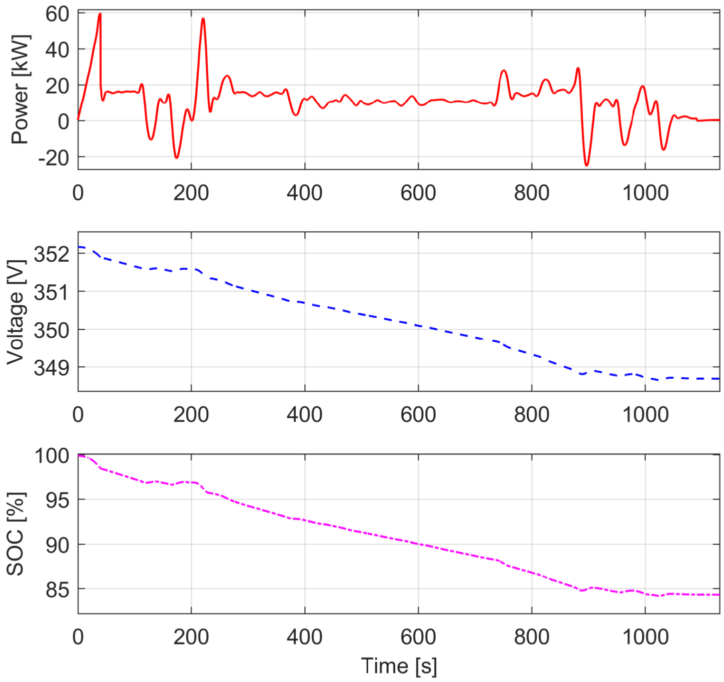

Fig. 11. Lower bound for TomTom Maps data Route 2

6 Conclusion and future work

noindent This paper constructed different driving cycles based on three API data and two different routes. A data collection framework is developed which gathers the same data from different API and process the data to generate realistic driving cycles. We divided the routes into slices using the route segmentation technique. The data contain the distance of the journey, the time taken for the whole journey, the average speed for the whole journey, and the waypoints. We developed a velocity model algorithm and introduced variations using a random function based on Gaussian normal distribution.

After introducing some randomness to the mean data extracted from the APIs, we used the locally weighted scatterplot smoothing function "LOWESS" in MATLAB to fit a smooth curve to the randomised data and eliminate any sharp edges. The data selection is based on data classification and statistical analysis. An electric vehicle's model based on Nissan leaf was implemented to calculate the power demand and the remaining range for each cycle.

The results show that the driving cycles are within the range and the vehicle's constraints are satisfied. Moreover, it simulates the driving patterns for each cycle. The results also show the variation between the different data sources and the times for the data collection. The state of charge estimation for each cycle and route varies for each route and data source. The route includes motorway driving, shows massive energy consumption when the vehicle manages to drive at the highest speed limit and shows less energy consumption when the traffic density restricts the speed. In contrast, the results also show less energy efficiency for city driving when the traffic is dense because the journey time is longer.

The proposed velocity model can be implemented to any other data source with more flexibility for the route segmentation. It can produce real-time velocity profiles construction without the need of collecting more data for more extended periods. It was not possible to integrate weather API and Traffic lights detection due to the restrictions in the map sources. However, this can be included when using open source API such as OpenStreetMaps API, even though it has less accuracy. Further laboratory experiments will be conducted in future to validate the results in this paper using Nissan leaf battery.

References

[1] John J Conti, Paul D Holtberg, Joseph A Beamon, A Michael Schaal, JC Ayoub, and James T Turnure. Annual energy outlook 2014. *US Energy Information Administration*, page 2, 2014.

[2] Kojo Menyah and Yemane Wolde-Rufael. Co2 emissions, nuclear energy, renewable energy and economic growth in the us. *Energy Policy*, 38(6):2911–2915, 2010.

[3] Xinkai Wu, David Freese, Alfredo Cabrera, and William A Kitch. Electric vehicles' energy consumption measurement and estimation. *Transportation Research Part D: Transport and Environment*, 34:52–67, 2015.

[4] Nina Juul and Peter Meibom. Road transport and power system scenarios for northern europe in 2030. *Applied Energy*, 92:573–582, 2012.

[5] Mike Knowles, Helen Scott, and David Baglee. The effect of driving style on electric vehicle performance, economy and perception. *International Journal of Electric and Hybrid Vehicles*, 4(3):228–247, 2012.

[6] Lei Zhu and Jeffrey D Gonder. A driving cycle detection approach using map service api. *Transportation Research Part C: Emerging Technologies*, 92:349–363, 2018.

[7] Google maps api (developers portal). https://cloud.google.com/maps-platform/. Accessed: 2019-09-03.

[8] Here Map. Here map apis. https://developer.here.com/products/maps/, 2019.

[9] TomTom. Tomtom map apis. https://developer.tomtom.com/products/maps-api/, 2019.

[10] Jun Bi, Yongxing Wang, Qiuyue Sai, and Cong Ding. Estimating remaining driving range of battery electric vehicles based on real-world data: A case study of beijing, china. *Energy*, 169:833–843, 2019.

[11] Nikhil Kaza. Urban form and transportation energy consumption. *Energy Policy*, 136:111049, 2020.

[12] Abbas Fotouhi, Rubiyah Yusof, Rasoul Rahmani, Saad Mekhilef, and Neda Shateri. A review on the applications of driving data and traffic information for vehicles energy conservation. *Renewable and Sustainable Energy Reviews*, 37:822–833, 2014.

[13] Xuewei Qi, Guoyuan Wu, Kanok Boriboonsomsin, and Matthew J Barth. Data-driven decomposition analysis and estimation of link-level electric vehicle energy consumption under real-world traffic conditions. *Transportation Research Part D: Transport and Environment*, 64:36–52, 2018.

[14] Cedric De Cauwer, Joeri Van Mierlo, and Thierry Coosemans. Energy consumption prediction for electric vehicles based on real-world data. *Energies*, 8(8):8573–8593, 2015.

[15] Guido Wager, Mark P McHenry, Jonathan Whale, and Thomas Bräunl. Testing energy efficiency and driving range of electric vehicles in relation to gear selection. *Renewable Energy*, 62:303–312, 2014.

[16] Enjian Yao, Zhiqiang Yang, Yuanyuan Song, and Ting Zuo. Comparison of electric vehicle's energy consumption factors for different road types. *Discrete Dynamics in Nature and Society*, 2013, 2013.

[17] Chris Bingham, Chris Walsh, and Steve Carroll. Impact of driving characteristics on electric vehicle energy consumption and range. *IET Intelligent Transport Systems*, 6(1):29–35, 2012.

[18] Tim J Barlow, S Latham, IS McCrae, and PG Boulter. *A reference book of driving cycles for use in the measurement of road vehicle emissions*. 2009.

[19] Hewu Wang, Xiaobin Zhang, and Minggao Ouyang. Energy consumption of electric vehicles based on real-world driving patterns: A case study of beijing. *Applied energy*, 157:710–719, 2015.

[20] Saad Alateef and Nigel Thomas. Battery models investigation and evaluation using a power demand generated from driving cycles. In *Proceedings of the 12th EAI International Conference on Performance Evaluation Methodologies and Tools*, pages 189–190, 2019.

[21] Emilia Silvas, Kobus Hereijgers, Huei Peng, Theo Hofman, and Maarten Steinbuch. Synthesis of realistic driving cycles with high accuracy and computational speed, including slope information. *IEEE Transactions on Vehicular Technology*, 65(6):4118–4128, 2016.

[22] Ying Yang, Qing Zhang, Zhen Wang, Zeyu Chen, and Xue Cai. Markov chain-based approach of the driving cycle development for electric vehicle application. *Energy Procedia*, 152:502–507, 2018.

[23] Peter Lipar, Irena Strnad, Martin Česnik, and Tomaž Maher. Development of urban driving cycle with gps data post processing. *Promet-Traffic&Transportation*, 28(4):353–364, 2016.

[24] A Esteves-Booth, T Muneer, H Kirby, J Kubie, and J Hunter. The measurement of vehicular driving cycle within the city of edinburgh. *Transportation Research Part D: Transport and Environment*, 6(3):209–220, 2001.

[25] Paolo Iora and Laura Tribioli. Effect of ambient temperature on electric vehicles' energy consumption and range: Model definition and sensitivity analysis based on nissan leaf data. *World Electric Vehicle Journal*, 10(1):2, 2019.

[26] Habiballah Rahimi-Eichi and Mo-Yuen Chow. Big-data framework for electric vehicle range estimation. In *IECON 2014-40th Annual Conference of the IEEE Industrial Electronics Society*, pages 5628–5634. IEEE, 2014.

[27] Ricardo Maia, Marco Silva, Rui Araújo, and Urbano Nunes. Electrical vehicle modeling: A fuzzy logic model for regenerative braking. *Expert systems with applications*, 42(22):8504–8519, 2015.

[28] Martin Murnane and Adel Ghazel. A closer look at state of charge (soc) and state of health (soh) estimation techniques for batteries. *Analog devices*, 2:426–436, 2017.