
How to Reduce Range Anxiety? The Impact of Digital Elevation Model Quality on Energy Estimates for Electric Vehicles

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Abstract

Reliable energy estimation methods are a very important step to address the range anxiety problem of electric vehicle adoption. Besides driving patterns and vehicle parameters, geographic information about elevation changes is one of the most important pieces of information to predict energy consumption. This paper presents a method to assess the impact of digital elevation model (DEM) quality on energy consumption estimation for electric vehicle routes. We demonstrate the use of this method by applying it to compare energy consumption estimates for 16,500 randomly generated routes based on three recently released open DEM datasets: NASA Shuttle Radar Topographic Mission (SRTM) version 3.0, EU-DEM and open government DEM data provided by the city of Vienna. Results show that energy consumption models tend to overestimate route energy consumption by a mean error of 2.9% and 15.8% respectively when lower-resolution DEMs are used to compute route elevation profiles. A spatial analysis of the error distribution shows that the mean error varies between different regions within the analysis area with bigger error values in the hills and in the city centre indicating that high-resolution elevation data is not only important in hilly and mountainous areas but also in dense urban environments.

1 Introduction

Rising prices for fossil fuels and concern about the impact of greenhouse gases from combustion engines has led to the development of new vehicle technologies. Particularly electric vehicles have received a lot of attention in research and development. Their general acceptance and sales numbers, however, are still low with shares of 0.3% of cars sold in the US in 2012 (GREEN ET AL 2014) and 0.21% of cars sold in Western Europe in 2012 (KVISLE 2013). One important problem electric vehicles face is their limited cruising range leading to what is known as *range anxiety*. To address this problem, it is crucial to provide the user with information about the current energy status and to reliably predict the energy required to complete planned routes. It is therefore necessary to develop solid methods to estimate energy consumption for routes prior to starting a trip.

In a related study, BACHOFER (2011) compares LIDAR data for Bavaria to Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and different versions of Shuttle Radar Topographic Mission (SRTM) data. The work focuses on energy estimates to provide a general overview of the driving range of electric vehicles by modelling the total energy consumption for travelling all the edges of the analysed street network. Results

for individual routes which are needed for operational route planning are not discussed in detail. He only reports that differences of more than 30% were observed for some route energy estimates.

Energy usage models for regular (i.e. combustion engine) and electric vehicles have been discussed for example in KONO ET AL. (2008) and PRINS ET AL. (2012) respectively. PRINS ET AL. (2012) compare the measured energy usage value on a test route to model predictions using elevation data from different sources: two GPS trackers and the USGS database. They report that all predictions overestimated the energy usage required for the route with values ranging between 22% for the worse GPS tracker and 7.9% for the better GPS tracker with the USGS elevation data scoring 11.3%. KONO ET AL. (2008) present a fuel consumption analysis for different geographic (mountainous or smooth) and traffic conditions (expressway or congestion), using elevation data provided by GSI of Japan with a spatial resolution of 50m. They present a comparison of fuel consumption factors in various geographic and traffic congestions which shows that base consumption and elevation change cause the biggest changes in the composition of total fuel consumption while fuel consumption due to friction, air drag and acceleration does not change much between scenarios.

A closely related problem is the problem of energy-optimal route planning for electric vehicle with recuperation, which is covered for example in BAUM ET AL. (2013) and JURIK ET AL. (2013). Due to the recuperation of electric energy, a negative edge weight is assigned to links running downhill. Basic routing algorithms such as Dijkstra's algorithm are not suitable to address this problem, because they require non-negative edge weights. Elevation data in both studies was derived from SRTM. The focus of these papers lies in developing algorithms which can quickly compute energy-optimal routes in real-world-sized networks. Results and discussions therefore focus on query time rather than evaluation of prediction results.

In this study we focus on the geographic information used in energy consumption models and evaluate the influence of different DEM quality on energy consumption estimates for routes in the city of Vienna. The remainder of this paper is structured as follows: Section 2 introduces the DEMs which were used in this comparison and describes the process used to generate the test route dataset. In Section 3 we describe the energy consumption model. Section 4 presents the results of our comparison before Section 5 discusses findings and Section 6 covers opportunities for future work.

2 Input Data and Preparation

This section gives an overview of DEMs and test routes which were used for the impact assessment of DEM quality on route energy estimation for electric vehicles. In this study, DEMs from NASA, European Environment Agency (EEA) and the city of Vienna were used to estimate the energy consumption of 16,500 randomly generated routes. Figure 1 provides a preview of the level of detail in the three DEMs.

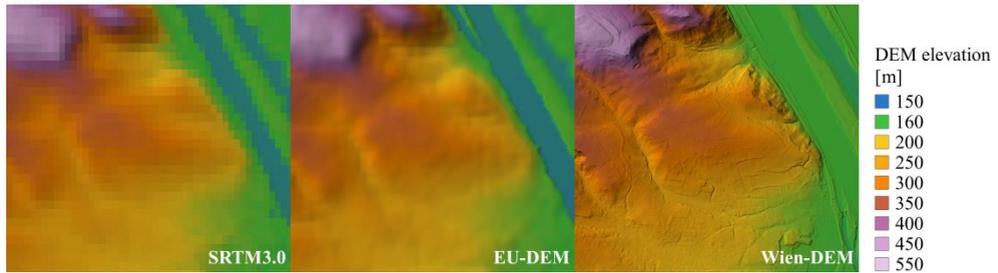


Fig. 1: Details of the hills and river side of northern Vienna in all three DEMs

NASA SRTM V3.0 (from now on referred to as SRTM3.0) was released on November 20th, 2013. SRTM3.0 has eliminated all voids found in previous versions with fill primarily from ASTER Global Digital Elevation Model Version 2, and secondarily from USGS GMTED2010 or USGS National Elevation Dataset. SRTM3.0 data is provided in WGS84 (EPSG:4326) with one-arc-second postings for the US and its territories, and three-arc-second postings (approximately 90m) for the world. (NASA 2013)

The EU-DEM is a digital surface model covering Europe, created in the course of the Copernicus programme funded by the European Union. The data was released in November 2013 (INSPIRE FORUM 2013) and is provided in EU-LAEA (EPSG:3035) at a resolution of 25m. EU-DEM is based on SRTM and ASTER GDEM data. The data is provided without formal validation so far. Publication of an independent statistical validation has been announced for the course of 2014. (EEA 2013)

The open government DEM dataset published by the city of Vienna (from now on referred to as Wien-DEM) is based on surface points, break lines (slope edges, shoreline), and airborne laser scanning data. It is provided as a regular vector point grid in WGS84 (EPSG:4326) and MGI/Austria GK East (EPSG:31256) at a resolution of 5m. The DEM is regularly updated with new data and artificial structures such as houses and bridges are excluded from this DEM (STADTVERMESSUNG WIEN 2013). The data is provided free of charge under a Creative Commons license via a Web Feature Service (WFS) with a reported limit of 300,000 features per request (OGD WIEN 2013b). In practice, it was necessary to request considerably smaller numbers of features using bounding boxes of 1km² size to successfully download the data from the WFS.

To achieve a good spatial distribution of test routes within the analysis area, we first generate a hexagonal grid with a cell size of 1km² covering Vienna. The set of random test routes is then generated by overlaying the hexagonal grid to the road graph, i.e. the GIP street network published by the city of Vienna (OGD WIEN 2013a). The road network is defined as a graph $G = (V, E)$, where the set of vertices V represents the intersections and the set of edges E represents the street segments. For each neighbouring pair of cells, ten unique pairs of randomly selected graph edges E are created. Cells containing fewer than ten edges are excluded from the analysis. The minimal air-line distance between edge pairs is defined as 800m, in order to avoid too short routes which would distort the analysis results.

For each edge pair, the central points of both start and end edge are then extracted and used as input for a shortest path routing. Each route is represented by an ordered set of all

geometry nodes of the graph edges comprising it. Subsequently, route elevation profiles are generated by extracting the DEM values at the node positions using nearest neighbour sampling. The resulting routes have a mean length of 2,109m (min: 802m, max: 15,754m, median: 1,830m). Only routes which are completely covered by all three DEM datasets are used in the following route energy consumption estimation.

3 Energy Consumption Modelling

This section presents the energy consumption model used to estimate energy consumption for individual routes. The test routes are computed based on the GIP street network as described in Section 2.

To estimate energy consumption on a route, we use a vehicle longitudinal dynamics model based on TREIBER & KESTING (2010). One part of this model estimates the required energy on the drive train. While in TREIBER & KESTING (2010) a model for a conventional combustion engine is used to estimate the overall energy consumption (amount of fuel), we in this study assume an electric motor. It is worth noting that the maximum efficiency of combustion engines is limited to a small operating range for torque and speed. Since this is not the case for electric engines, efficiency is much less dependent on current speed and torque and therefore can be assumed as rather constant.

The total power estimate is composed of power to overcome acceleration resistance (P_{kin}), rolling resistance (P_{res}), wind resistance (P_{air}), and elevation changes (P_{pot}) as well as the power (P_0) for appliances such as heating, air conditioning and lights. The required power on the drive train for a moving a vehicle therefore is

$$P_{drive} = \max(0, P_{kin} + P_{res} + P_{air} + P_{pot}). \quad (1)$$

Since in this study we focus on the influence of different DEM quality on energy consumption estimates, we are mainly interested in changes to the term related to potential energy $P_{pot} = mg\Delta h$ where m is the mass of the vehicle, g is gravity, and Δh is the elevation difference.

On downhill sections, the potential energy can outweigh acceleration, rolling and wind resistance and excessive power can be recuperated back to the battery up to a certain maximum. Therefore recuperation power is described by

$$P_{rec} = \min(0, P_{kin} + P_{res} + P_{air} + P_{pot}). \quad (2)$$

From (1) and (2) it is clear that either P_{drive} or P_{rec} is not null, which means for the electric engine to be operated either as a motor or as a generator with different conversion efficiency rates. The total energy which has to be provided by the battery can be described as the difference between total energy spent and recuperated energy

$$E = [P_{drive}/\alpha_{drive} + \max(-P_{max}, P_{rec}\alpha_{rec}) + P_0] \Delta t, \quad (3)$$

where α_{drive} and α_{rec} are the efficiency rates of the power train (composed of efficiency rates for motor/generator, gear unit, charging and discharging) depending on the direction of energy flow and Δt is the time span. If E is negative, energy will be restored to the battery. In this study, α_{drive} is set to 0.78, α_{rec} to 0.77 (SCHWINGSHACKL 2009) and the

maximum recuperation power P_{max} is 10kW. The value for α_{rec} is dependent on the type of vehicle and strategy for regenerative braking.

This energy consumption model (3) has been applied to 16,500 routes which are covered by all three DEM datasets. For this evaluation, a typical average urban travelling speed of 35km/h is assumed and the speed is kept constant on the whole route to keep the non-elevation-dependent parameters fixed since this evaluation focuses completely on the impact of DEM quality on energy estimates.

4 Energy Estimates

This section presents the results of a statistical evaluation of the model (3) predictions. Table 1 shows a comparison of indicators for the estimates based on all three DEMs. The data shows that the minimum energy consumption values for all three DEMs are negative meaning that electric vehicles would be able to recuperate energy on some of the test routes. The mean energy consumption ranges between 13.01 and 15.06kWh per 100km with the lowest values based on Wien-DEM and the highest values based on SRTM3.0. The low overall energy consumption values can be attributed to the constant low vehicle speed of 35km/h which is used for the energy estimation.

Table 1: Energy consumption estimations

	SRTM3.0	EU-DEM	Wien-DEM
min kWh per 100km	-8.76	-12.50	-14.67
max kWh per 100km	67.29	64.73	66.37
mean kWh per 100km	15.06	13.40	13.01
standard deviation kWh per 100km	6.41	6.19	6.31
median kWh per 100km	13.86	12.69	12.36

Next, we compare energy estimates based on EU-DEM and SRTM3.0 to energy estimates based on Wien-DEM. For the sake of this study, the estimates based on Wien-DEM serve as reference values because Wien-DEM is the most detailed DEM in the sample and it is not practical to collect real-world energy consumption data for a test route set of this size. The results of this comparison as summarized in Table 2 show that energy estimates based EU-DEM and SRTM3.0 tend to be higher by 0.38 and 2.06kWh, respectively. This corresponds to errors of 2.9% and 15.8% relative to the Wien-DEM mean energy consumption rate of 13.01kWh per 100km.

Figure 2 shows the correlation of average slope on the route and associated energy consumption. The black line shows the predicted energy consumption on a virtual route with a constant slope which serves as a reference. The graph clearly shows that – except for a small number of outliers – all energy estimates for real-world routes are equal or higher than the energy estimate for the virtual route with constant slope and estimates based on SRTM3.0 tend to deviate most from the reference line.

Table 2: Energy estimation errors based on EU-DEM and SRTM3.0 (Percentage values refer to the Wien-DEM mean energy consumption rate of 13.01kWh per 100km.)

	EU-DEM – Wien-DEM		SRTM3.0 – Wien-DEM	
min error	-19.01	-146.1%	-13.25	-101.8%
max error	17.36	133.4%	34.23	263.0%
mean error	0.38	2.9%	2.06	15.8%
standard deviation of errors	1.64	12.6%	2.85	21.9%
RMSE	1.69	13.0%	3.52	27.0%
mean absolute error	1.15	8.8%	2.36	18.1%

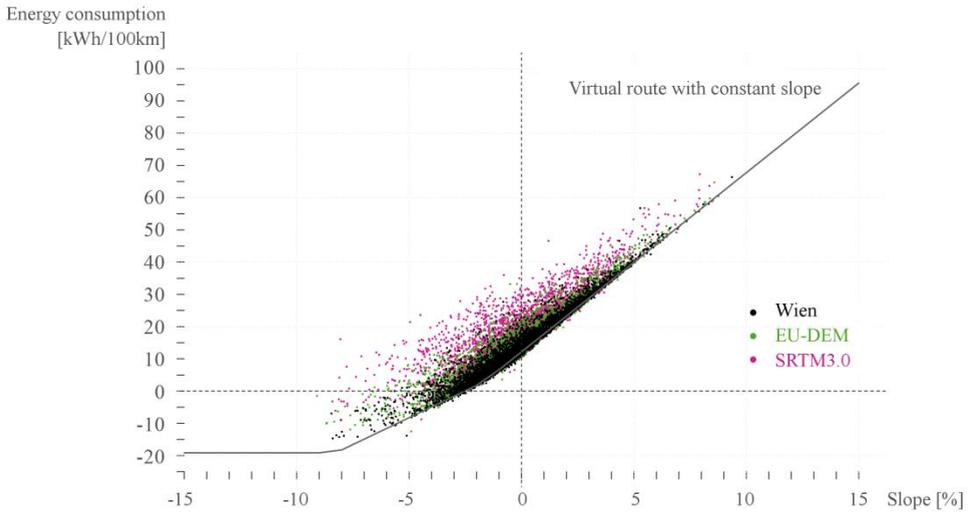


Fig. 2: Energy consumption values over average route slope

The evaluation so far represents a summary of the results for all routes within the analysis area. Since DEM error values correlate with terrain characteristics such as slope and aspect (GOROKHOVICH & VOUSTIANIOUK 2006), we also compute the spatial distribution of energy estimation errors. Figure 3 shows the spatial distribution of energy estimation errors of EU-DEM and SRTM3.0 in the analysis area.

Each line in Figure 3 represents the mean energy estimation error of the routes between the corresponding ordered pair of grid cell neighbours. Obviously, the errors are dependent on the sequence of start and end cell. Therefore, all lines are drawn with an offset to the right from the centre line to distinguish between the two possible directions. Overestimation is shown in pink, underestimation in green. Wider lines represent bigger errors.

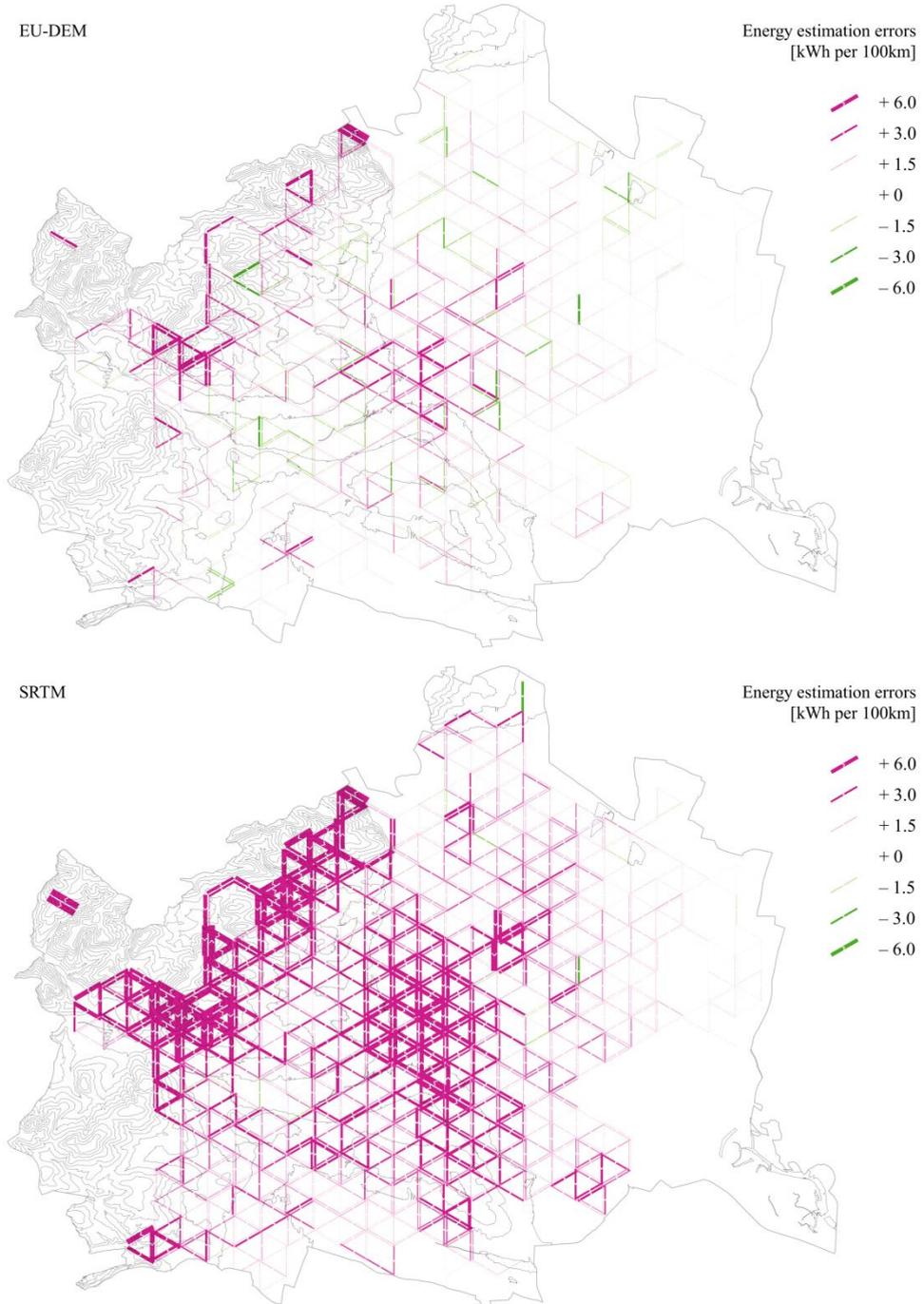


Fig. 3: Spatial distribution of energy estimation errors based on EU-DEM and SRTM3.0

The background of both maps shows contour lines at 25m intervals derived from Wien-DEM which serve as an indicator of the terrain characteristics in the different regions of Vienna. While the eastern regions are dominated by flat terrain of the Vienna Basin, the western regions are dominated by the north-eastern foothills of the Alps. As expected, the maps confirm that errors in the predictions based on SRTM3.0 are bigger than in the predictions based on EU-DEM and in both cases the biggest error values are located in the hills in the north-west and in the city centre.

5 Discussion

The statistical analysis results as summarized in Tables 1 and 2 show that energy estimates tend to be higher when the estimation is based on EU-DEM or SRTM3.0 than when the estimation is based on the high-resolution Wien-DEM. The reason for this behaviour becomes clearer when we compare individual route profiles for the same route on different DEMs. An example is depicted in Figure 4. It shows all three profiles of one of the test routes in the north-western hills. The profiles based on EU-DEM and SRTM3.0 clearly exhibit more elevation changes – including steep drops and rises – than the profile based on Wien-DEM which is smoother and overall more realistic since roads for vehicle traffic are built with moderate slopes rather than abrupt changes. The error based on EU-DEM is generally smaller than the error based on SRTM3.0 because the SRTM3.0 profile exhibits the biggest and most sudden elevation changes as can be seen in Figure 4. This behaviour can be observed for the vast majority of routes.

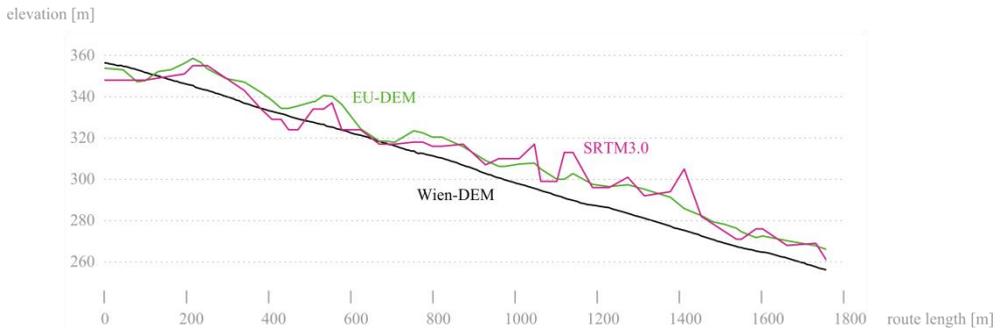


Fig. 4: Route profiles of a sample route, energy estimate difference: +12.96kWh (EU-DEM) and +31.94kWh (SRTM3.0)

In the spatial analysis of error distributions, two regions exhibit higher errors than the rest of the analysis area: the hills in the north-west and the city centre. These results are consistent with other studies on DEM accuracy such as GOROKHOVICH & VOUSTIANIOUK (2006) who show that SRTM error values correlate with terrain characteristics such as slope and aspect, and COLOSIMO ET AL. (2009) who evaluate SRTM and ASTER data and show higher errors in urban and forested areas compared to more open landscapes. Furthermore, since EU-DEM is based on SRTM and ASTER data, similarities in the spatial distribution of errors are not unexpected.

The results of this study indicate that – in areas within Europe where no high-resolution elevation data is available – it is recommendable to use EU-DEM instead of SRTM data for route energy consumption modelling. Using these DEM, one should be aware that energy consumption tends to be overestimated. For the test route set in this study, mean errors of +2.9% and +15.8% were observed using EU-DEM and SRTM3.0 respectively. The spatial analysis furthermore shows that high-resolution elevation data is not only important in hilly and mountainous areas but also in dense urban environments.

6 Outlook

In this study, route elevation profiles were generated using nearest neighbour sampling to extract elevation values for the route geometry nodes. Sampling at geometry nodes is the most commonly used approach described in related studies but most do not report on which sampling method was employed. The current study therefore serves as a base line reference. Further work will look into possible improvements by sampling elevation values in regular intervals along the route and by applying more sophisticated methods such as bilinear resampling.

One open issue with route profiles derived from Wien-DEM currently is that they contain sudden drops and jumps at bridges and tunnels since the DEM does not include artificial and underground structures. To handle this issue more gracefully and improve energy predictions for such routes, alternative approaches as shown for example by SCHILLING ET AL. (2009) will be implemented and evaluated.

Further work is planned which will compare energy consumption estimates to data collected by test vehicles. Battery state of charge and capacity information will be used to derive ground truth data about energy consumption. The model described in section 3 will then be applied to the vehicle GPS data which makes it possible to compare estimation results and observed energy demand.

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