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IMPACT OF TOPOGRAPHIC DATA ON ELECTRIC VEHICLE ENERGY PREDICTION

Purpose. To assess the impact of sampling frequency and topographic data sources on the accuracy of electric vehicle (EV) driving energy consumption calculations using standardized test protocols.

Methodology. The study calculates the driving energy consumption of an EV based on a theoretical model that incorporates the topographic profile of the route and the driving mode defined by the selected test protocol. The analysis was conducted for several alternative paths of the same route along European roads under varying discretization steps and topographic data sources.

Findings. It was established that the sampling frequency and accuracy of topographic data significantly affect the results of energy consumption calculations. A range of discretization steps ensuring acceptable accuracy while reducing computational load was identified. Errors for different data sources were quantified depending on the characteristics of the route's topographic profile.

Originality. The study establishes the relationship between the accuracy of electric vehicle driving energy calcula-tions and both the sampling frequency and the selected topographic data source, taking into account topographic profile. Threshold conditions were identified under which increasing the discretization step or using less accurate datasets does not lead to significant errors.

Practical value. The obtained results enable a well-grounded selection of the optimal discretization step and topographic data source to improve the accuracy of energy consumption forecasting for passenger EVs during route planning.

Keywords: *electric vehicles, route planning, topological profile, WLTP, discretization, topological bases*

Introduction. The aim of this study is to perform a theoretical analysis of the influence of both the source of route topographic data and the sampling frequency of the points describing the route on the calculation of electric vehicle (EV) driving energy consumption.

Topographic data for three alternative routes between points A and B along European roads were obtained from open-access datasets: SRTM1, SRTM3, and ODP1.

To evaluate the impact of data type and sampling frequency on driving energy prediction, one of the routes was selected, and the effect of varying discretization steps on calculation accuracy was analyzed.

The assessment of driving energy consumption was carried out in accordance with the Worldwide Harmonized Light Vehicles Test Procedure (WLTP).

Based on the results, the relationship between energy consumption error accumulation and discretization frequency was established. Additionally, the accuracy of different datasets was evaluated relative to ODP1 for routes of varying lengths.

Literature review. In recent years, the number of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) has increased significantly worldwide [1, 2]. This trend is driven by global strategies aimed at reducing CO_2 and particulate matter emissions into the atmosphere. In 2023, approximately one in four newly sold vehicles globally was electric [3]. In Norway, this share exceeded 90 %, while in China it approached 40 % (based on 2023 data). The rate of electric vehicle (EV) adoption in Norway is the highest in the European region. This is attributed to a national target set by the Norwegian parliament, mandating that all new cars sold by 2025 must have zero emissions (either electric or hydrogen-powered) [4]. Overall, the global share of EVs among all newly sold vehicles in 2023 reached 18 %, representing a 4 % increase compared to the same period in 2022.

In parallel with the expansion of the electric vehicle fleet, the infrastructure of modern cities is evolving [5], and related fields are also actively developing. This includes research focused on improving not only environmental but also technical safety aspects of EV operation [6]

Despite substantial governmental support aimed at encouraging consumers to adopt electric vehicles – through discounts and incentives – the pace of mass adoption is slowing due to key limitations of EVs, namely their limited driving range and lengthy charging times [7, 8].

A major distinction between electric vehicles and internal combustion engine (ICE) vehicles is the presence of a regenerative braking system. This system enables the recovery of a portion of the kinetic energy generated during braking and its return to the electric vehicle's battery [9, 10].

Key factors influencing driving energy consumption include driving modes, road infrastructure, and route topography [11, 12].

One of the tools that enables users of any type of vehicle to select a route is the interactive Google Maps service [13]. This platform allows drivers to choose from three suggested routes, depending on the criterion that is most relevant to them. By default, the recommended route is the one with the highest average speed, i.e., the shortest travel time.

However, the fastest route is not always the most energy-efficient due to the influence of the aforementioned factors. For instance, the route's infrastructure and the associated driving patterns affect the vehicle's energy efficiency regardless of the powertrain type – EV or ICE [14, 15].

To compare the efficiency of conventional vehicles and electric vehicles of various models and manufacturers, standardized test protocols are employed [16]. One such protocol is the WLTP, which includes the Worldwide Harmonized Light Vehicles Test Cycle (WLTC). Depending on the test class, this procedure categorizes passenger vehicle driving into several characteristic speed profiles: Low, Medium, High, and Extra-High. This classification reflects differences in driving behavior in urban areas, suburban traffic, intercity roads, and highways.

The WLTP-based assessment involves testing the vehicle under a specified driving pattern on controlled test tracks, allowing energy consumption to be measured under those conditions. However, such conditions do not account for one crucial factor influencing energy use – the road profile. While the horizontal profile (e.g., curves) primarily affects speed and therefore energy consumption indirectly, the vertical profile (e.g., inclines and declines) directly influences energy consumption, as it is associated with changes in the vehicle's potential energy.

Route profile consideration must account for the characteristics of the selected route, the vehicle, and the driving mode. If the driving mode is defined by a standardized test protocol (e.g., WLTP), it becomes possible to analytically calculate energy consumption along the selected route while incorporating its topographic features.

Accurate data on the route profile is essential for predicting EV driving energy losses, as the number of ascents and descents, as well as their slope angles, directly influence the calculation of driving range. The accuracy of terrain topography reconstruction and the sampling frequency of the route are key factors that determine the reliability of the obtained data.

A wide range of open-access topographic datasets is available globally, including NASA's SRTM (Shuttle Radar Topography Mission), Copernicus DEM (Digital Elevation Model), ALOS World 3D (AW3D30), and ODP1 (Sonny's LiDAR DTMs), among others. These datasets differ primarily in three parameters: coverage area, resolution, and nominal horizontal and vertical accuracy. These parameters depend on the satellite sensor type and the data acquisition technology [17, 18].

For the calculations in this study, three open-access topographic datasets were selected: SRTM1, SRTM3, and ODP1 [19, 20]. Their nominal characteristics are presented in Table 1.

The sampling frequency of the route, defined as the distance between two topographic data points along the trajectory, determines the accuracy of the reconstructed route curve on the latitude/longitude plane and the level of detail in the topographic profile.

A higher sampling frequency ensures better route reconstruction and, consequently, higher accuracy of the calculations.

Conversely, a low sampling frequency results in distortion of the route shape, which affects the number and geometry of turns as well as the identification of the number and steepness of ascents and descents.

Purpose. The review of the literature indicates that most authors focus on evaluating electric vehicle energy consumption while considering various factors that influence driving efficiency. However, the impact of the spatial sampling frequency of the route and the choice

Table 1

Characteristics of the Topographic Datasets SRTM1, SRTM3, and ODP1 [19, 20]

Dataset	Acquisition Years	Released Years	Agency	Coverage	Resolution	Sensor	Method	Nominal Vertical Accuracy	Nominal Horizontal Accuracy
SRTM1	2000	2003, updated 2014	NASA, NGA	60°N – 60°S land areas	1 arc-second (~30 m)	C-band radar	Interferometric SAR	~16 m (90 % confidence)	~20 m
SRTM3	2000	2003	NASA, NGA	60°N – 60°S land areas	3 arc-seconds (~90 m)	C-band radar	Interferometric SAR	~16 m (90 % confidence)	~40 m
ODP1	2016–present	2016–present	Sonny	Western Europe, Iceland	1 arc-second (~30 m)	LiDAR, photogrammetry, SRTM fusion	Airborne Laser Scanning (ALS) & SRTM resampling	~1–5 m (depending on source)	~5–20 m

of topographic data source on the accuracy of such calculations has received limited attention.

Since topographic datasets differ in resolution, accuracy, and spatial coverage, these characteristics can significantly affect the results of EV energy consumption calculations.

Compared to existing studies, this work proposes an approach for assessing the accuracy of driving energy consumption calculations by accounting for both the route sampling frequency and the selected topographic data source.

Methods. A method for predicting the most energy-efficient route among a set of alternatives, considering topographic characteristics, is presented in [21]. The described approach allows the selection of a route that minimizes driving energy consumption.

The calculation is based on the evaluation of natural resistive forces acting on the electric vehicle along a given route, while accounting for topographic variations expressed as the slope angle relative to the horizontal plane.

The input topographic data include elevation above sea level (m) and coordinates (latitude/longitude, °), which are exported from the open-source mapping service GPS Visualizer [22]. The step size of either fixed or adaptive sampling (i.e., the distance between data points) is determined by the source of the input data.

The latitude and longitude geodata are exported from Google Earth (GE) and remain constant throughout the calculation cycle. To generate datasets with different fixed sampling intervals (1, 2, 5, and 10 meters), intermediate points between the base GE coordinates were computed using linear interpolation.

The topographic data are then aligned with the interpolated coordinates using the GPS Visualizer service, which utilizes the array of latitude/longitude points as input. Elevation values for the selected route are retrieved from open-access topographic datasets: ODP1, SRTM1, and SRTM3.

$$\theta_i = \arcsin\left(\frac{h_i - h_{i-1}}{\Delta l_i}\right). \quad (1)$$

The slope angle over a segment of length l_i between two consecutive points at the selected discretization step can be determined using the latitude and longitude of the $(i-1)^{th}$ and i^{th} route points, along with their respective elevations h_{i-1} and h_i according to Equation (1).

$$A_i = (F_{U,i}) \vee F_{D,i})l_i. \quad (2)$$

The mechanical work over the corresponding i^{th} segment of length l_i is calculated using Equation (2). Depending on the sign of the slope angle, the average mechanical resistive force is defined as follows: for a positive angle, $F_{U,i}$ is applied (uphill resistance); for a negative angle, $F_{D,i}$ is applied (downhill resistance).

$$A_r = \sum A_i = \sum (F_{U,i} \vee F_{D,i})l_i. \quad (3)$$

The total mechanical work along the entire route (path) is calculated using Equation (3), J/m

$$w_r = \frac{1}{L_r}\sum A_i = \frac{1}{L_r}\sum (F_{U,i} \vee F_{D,i})l_i = = \frac{1}{L_r}\sum (A_{U,i} \vee A_{D,i}), \quad (4)$$

where $A_{U,i} = F_{U,i}l_i$ is the work required to overcome the mechanical resistive force $F_{U,i}$ when moving uphill along the i^{th} segment of the route; $A_{D,i} = F_{D,i}l_i$ is the work required to overcome the mechanical resistive force $F_{D,i}$ when moving downhill along the i^{th} segment of the route.

The specific work along the route, calculated over the total profile length $L_r = \sum l_i$, is determined using Equation (4).

To obtain the values of $A_{U,i}$ or $A_{D,i}$, the methodology presented in [21], can be applied for any driving mode defined by a test cycle. The relationship between the specific mechanical energy consumption and the road slope angle for a Nissan Leaf AZE0 passenger electric vehicle under the WLTC Class 3b test cycle is provided in [21]. The calculations were performed under conditions of no wind and maximum tire–road adhesion. The energy recovered during regenerative braking was not considered in the calculation of specific energy consumption.

Additionally, centrifugal forces acting on the vehicle during cornering were also neglected.

Results. ***Influence of route profile sampling frequency on driving energy consumption calculation.*** To describe the route, including its curvature, Google Earth employs an adaptive discretization algorithm that increases the number of points in curved sections and reduces them in straight segments.

The use of a constant discretization step is an alternative route description method, in which a fixed interval between points is set from a predefined range. In this study, the following set of fixed sampling intervals was selected to evaluate the impact of discretization step on driving energy consumption calculations: 1, 2, 5, 10, 20, 50, 100, 200, 500, and 1,000 meters.

The calculation results obtained for adaptive discretization and various fixed step values are compared against the results for the 1-meter discretization step. This value is selected as the reference, as it provides the most accurate representation of both the route shape and the topographic profile due to the smallest spacing between points in the entire set.

To assess the impact of sampling frequency on energy consumption calculations using the proposed methodology [21], three alternative route paths between points A and B, suggested by the Google Earth service, were selected.

The route through the city of Thun, Switzerland, shown in Fig. 1, is plotted between point "A" (46.76172, 7.599228) and point "B" (46.717836620971305, 7.553759509185305), and includes three alternative ways: R1-R3. The parameters of these alternative ways are presented in Table 2.

The calculation results for the specified range of discretization steps, excluding the effect of centrifugal forces acting on the electric vehicle during cornering, are presented in Table 3. The calculations were performed using the parameters of the Nissan Leaf AZE0 BEV vehicle operating under the standard WLTC Class 3b driving cycle.

Fig. 2 presents the route projection on the latitude/longitude plane. Discretization steps of 2–50 meters, as well as the adaptive discretization used by Google Earth (GE), result in route length deviations within the range of 0.02–0.084 km. The route shape on the latitude/longitude plane and the topographic profile (Fig. 5) show

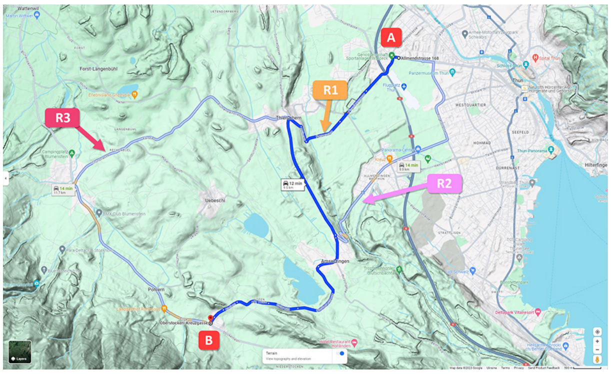

Fig. 1. Selected route, where A and B are the start and end points of the route, and Way R1—Way R3 represent the alternative ways

Table 2

Parameters of the alternative ways (Way R1—Way R3) of the route

Way	L_w, km	t_w, min	V_{aw}, km/h
R1	9.5	12	47.5
R2	9.9	14	42.4
R3	11.7	14	50.2
Where: L_w – way length, m; V_{aw} – average speed, km/h; t_w – stated travel time for the way, min			

only minor deviations compared to the 1-meter reference step. In these cases, the error in driving energy calculation ranges from 4.451 to 8.629 % (Table 3).

For discretization steps of 100–1,000 meters, the route length difference increases to 0.143–1.156 km, while the error in driving energy calculation ranges from 8.629 to 16.139 %.

Within this range, the topographic profile (Fig. 5) and route trajectory (Fig. 3) are significantly distorted compared to the 1-meter discretization. This distortion is caused by a reduction in the number of identified turns (Figs. 3, 4) and the omission of local ascents and descents.

The analysis of the logarithmic scale of discretization step variation (Fig. 6) for Way R1 shows that the

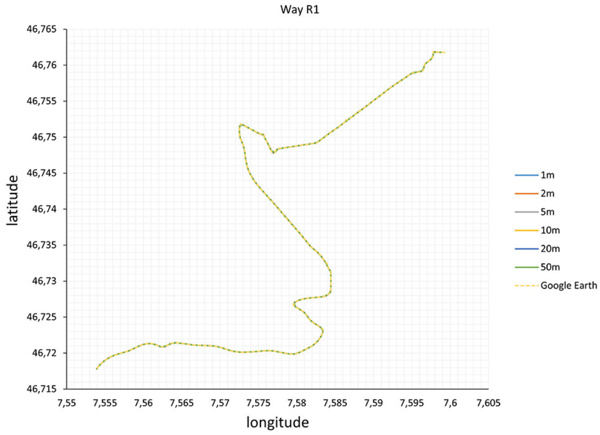

Fig. 2. Way R1 with fixed discretization steps: 1, 2, 5, 10, 20, 50 meters, and adaptive discretization by Google Earth

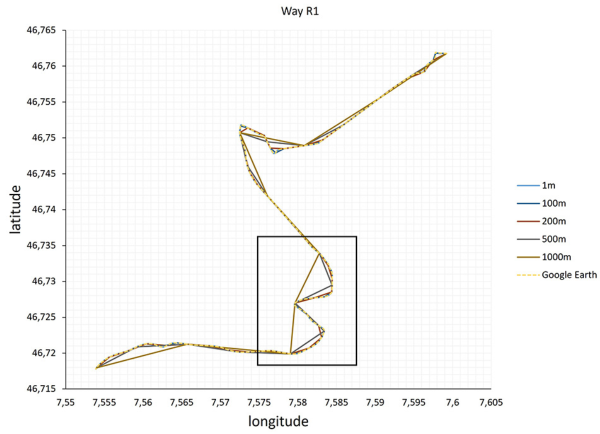

Fig. 3. Way R1 with discretization steps: 100, 200, 500, 1,000 meters, and Google Earth adaptive discretization

gradient of change in mechanical driving energy within the 10–100-meter interval differs significantly – by a factor of 3 to 3.5 – from that observed in the 1–10 meter and 100–1,000-meter intervals.

Moreover, the error within the 10–100-meter range does not exceed 2.17 % relative to the value at the 10-meter step.

Table 3

Electric vehicle driving energy consumption for different discretization steps along Way R1

Step, m	L_w, km	ΔL_w, km	A_r, kJ	ΔA_r, kJ	Error, %
Adaptive discretization					
GE	9.509	–0.025	8,246.828	568,678	6.45
Fixed discretization					
1	9.484	0	8,815.506	0	0
2	9.482	0.002	8,417.617	397.889	4.451
5	9.478	0.006	8,297.885	517.621	5.871
10	9.47	0.014	8,246.892	568.614	6.45
20	9.46	0.024	8,178.532	636.973	7.22
50	9.4	0.084	8,126.622	688.884	7.814
100	9.341	0.143	8,054.756	760.75	8.629
200	9.077	0.407	7,898.979	916.528	10.396
500	8.779	0.705	7,655.416	1,160.09	13.159
1,000	8.328	1.156	7,392.726	1,422.78	16.139
L_w – total way length, km; ΔL_w – difference in work-related length, kJ; A_r – total mechanical driving energy along the way, kJ; ΔA_r – difference in mechanical driving energy, kJ; Error – deviation relative to ODP1 dataset, %					

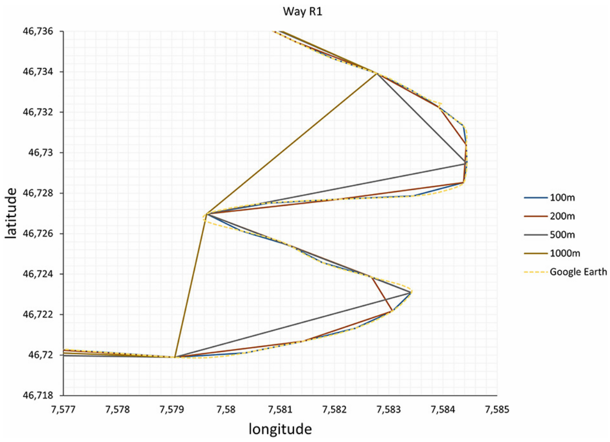

Fig. 4. Segment of Way R1 with discretization steps: 100, 200, 500, 1,000 meters, and Google Earth adaptive discretization

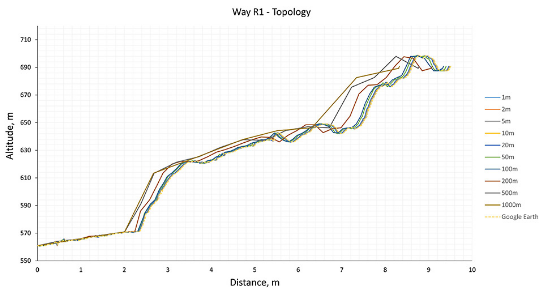

Fig. 5. Variation of the topographic profile of Way R1 depending on the discretization frequency

Relative to the reference mechanical driving energy obtained with a 1-meter discretization step, the result for the 100-meter step shows an error of approximately 8.6 %.

Thus, selecting a discretization step within the range of 10–100 meters ensures that the error remains below 8.6 %.

Impact of the route topography dataset on driving energy consumption calculation. In addition to route discretization frequency, the source of topographic data also affects the accuracy of driving energy calculations.

The impact of different topographic data sources on the results for Ways R1–R3 (Fig. 1) is assessed using the methodology from [21] for the Nissan Leaf AZE0 electric vehicle.

The calculation results based on three open-access topographic datasets – ODP1, SRTM1, and SRTM3 – are presented in Table 4.

The distribution of driving energy along the entire Way R1, depending on the topographic profile, is shown in Fig. 8. An analysis of the elevation profile reveals significant discrepan-cies—approximately 10–20 meters—in altitude values along certain segments of the route.

A specific segment of Way R1 from Fig. 8 is shown sepa-rately in Fig. 9.

The results of electric vehicle driving energy consumption calculations along Way R1 are presented in Table 4. The error was calculated relative to the reference data from the ODP1 dataset.

Based on the calculation results (Table 4), it can be concluded that differences in the topographic profile shape along Way R1 with a total length of 9.5 km (Fig. 8), caused by variations in topographic data, lead to an error of approximately 1.9 %.

However, when analyzing the results for a 0.581 km segment of Way R1 (Fig. 9), which exhibits significant discrepancies in the elevation profile, the error increases to 10.68 % for the SRTM3 dataset (Table 5).

The error in driving energy calculation for Way R2 (Fig. 10), which has a total length of 8.57 km (Table 4), is approxi-mately 2 % relative to the ODP1 dataset. When examining the results for a 0.478 km segment of Way R2 (Fig. 11), consistent differences in the topographic profile are observed during the uphill section, with variations ranging from 6 to 10 meters above sea level.According to the calculation results (Ta-

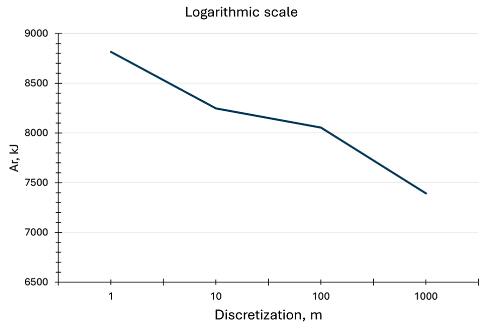

Fig. 6. Logarithmic scale of discretization step variation versus driving energy consumption

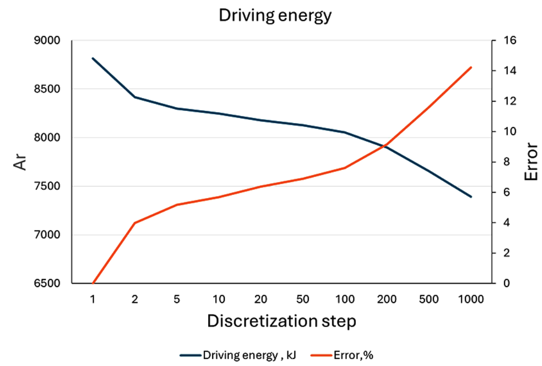

Fig. 7. Accumulation of driving energy calculation error with respect to discretization frequency

Table 4

Driving energy calculation results for Ways R1–R3 using the ODP1, SRTM1, and SRTM3 datasets

Database	Way R1			Way R2			Way R3		
	A_r, kJ	Error, %	L_w, km	A_r, kJ	Error, %	ΔL_w, km	A_r, kJ	Error, %	ΔL_w, km
ODP1	8,248.29	0	8.24	8,570.81	0	8.57	9,709.58	0	9.7
SRTM1	8,287.03	0.469		8,588.62	0.207		9,859.19	1.54	
SRTM3	8,404.07	1.888		8,599.50	0.334		9,714.81	0.05	
A_r – total mechanical driving energy along the way, kJ; Error – deviation relative to the ODP1 dataset, %; L_w – total way length, km									

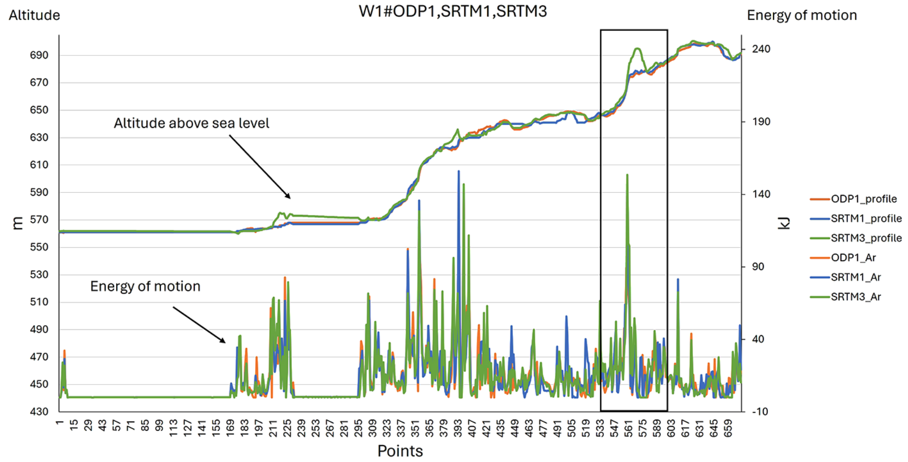

Fig. 8. Driving energy distribution along Way R1 for the ODP1, SRTM1, and SRTM3 datasets

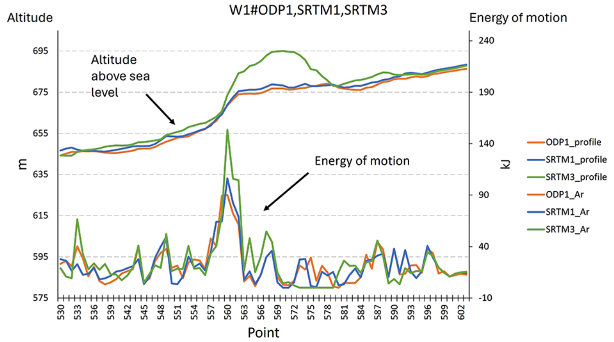

Fig. 9. Driving energy distribution along a segment of Way R1 for the ODP1, SRTM1, and SRTM3 datasets

ble 6), such variation results in an error of approximately 1 %.

According to the calculation results (Table 6), such variation results in an error of approximately 1%.

The driving energy calculation results for Way R3, with a total length of 9.7 km (Fig. 12) show an error of 1.54 % (Table 4). For a 0.228 km segment of Way R3 (Fig. 13), which is characterized by a consistent difference in the topographic profile (4.9–5 meters) while traveling over flat terrain without pronounced ascents or descents, the error of other datasets relative to ODP1 is 1.1 % (Table 7).

Differences in the topographic profiles of the SRTM1 and SRTM3 datasets relative to ODP1 over route lengths

Table 5

Driving energy calculation results for the selected segment of Way R1

Database	Way R1		
	A_{rv}, kJ	Error, %	L_{wv}, km
ODP1	1,616.02	0	0.581
SRTM1	1,609.76	–0.387	
SRTM3	1,788.77	10.689	

A_{rw} – total mechanical driving energy along the route segment, kJ; Error – percentage deviation relative to the ODP1 dataset, %; L_{wv} – total length of the route segment, km

Table 6

Driving energy calculation results for the selected segment of Way R2

Database	Way R2		
	A_{rw}, kJ	Error, %	L_{wv}, km
ODP1	1,455.53	0	0.478
SRTM1	1,468.74	0.908	
SRTM3	1,447.51	–0.55	

A_{rw} – total mechanical driving energy along the route segment, kJ; Error – percentage deviation relative to the ODP1 dataset, %; L_{wv} – total length of the route segment, km

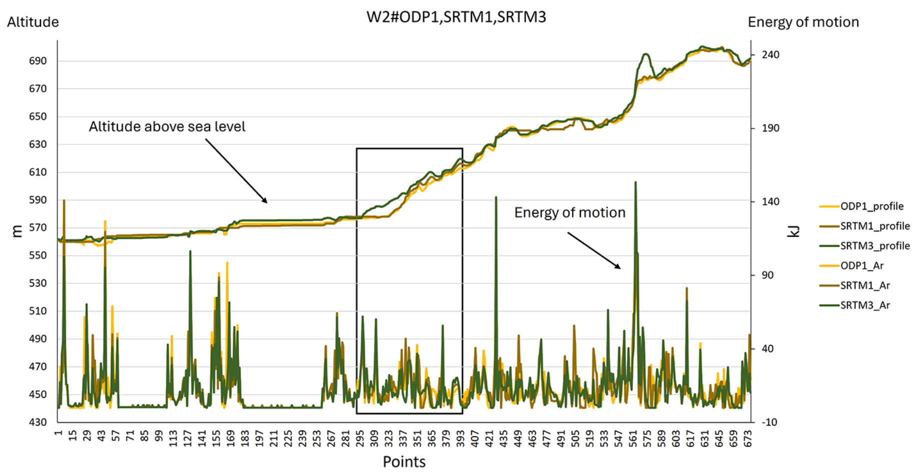

Fig. 10. Driving energy distribution along Way R2 for the ODP1, SRTM1, and SRTM3 datasets

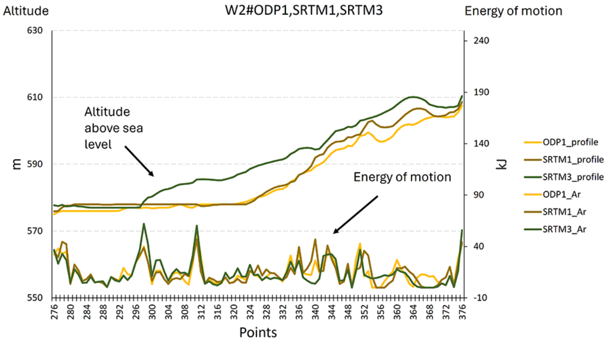

Fig. 11. Driving energy distribution along a segment of Way R2 for the ODP1, SRTM1, and SRTM3 datasets

Table 7

Driving energy calculation results for the selected segment of Way R3

Database	Way R3		
	A_r, kJ	Error, %	L_{wv}, km
ODP1	1,868.35	0	0.228
SRTM1	1,868.19	–0.00861	
SRTM3	1,889.25	1.1189	

A_{ry} – total mechanical driving energy along the route segment, kJ; Error – percentage deviation relative to the ODP1 dataset, %; L_{wv} – total length of the route segment, km

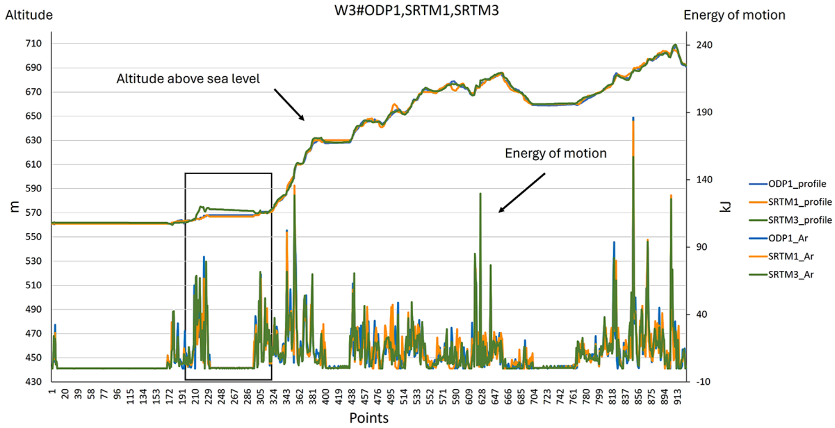

Fig. 12. Driving energy distribution along Way R3 for the ODP1, SRTM1, and SRTM3 datasets

of 8.24–9.7 km result in an error not exceeding 1.9 % (Table 4). On shorter route segments ranging from 0.228 to 0.581 km, the largest deviations in the topographic profile are observed for the SRTM3 dataset.

When the profile deviation remains consistent over flat terrain, the error does not exceed 1.1 %, and during uphill sections, it remains below 0.98 %. The highest recorded error—approximately 11 % – was observed on a segment with an incline and significant peak elevation deviations (10–20 meters) in the topographic data.

Conclusions.

1. The most accurate value of mechanical work for traversing Way R1 is obtained with the smallest discretization step, which in this case is 1 meter. Notably, the adaptive discretization step used by the GE dataset (for the selected route) demonstrates accuracy comparable to that of a fixed 10-meter step.

2. Considering the gradient of change in driving energy across the selected range of discretization steps, it can be noted that choosing a step within the 10–100-meter range results in an error no greater than 2.17 % relative to the value obtained at a 10-meter step, and up to 8.6 % relative to the reference driving energy calculated with a 1-meter discretization step.

3. Selecting a discretization step within the range of 10–100 meters is reasonable from the standpoint of reducing the computational load on the system, which increases as the step size decreases.

4. The error of the SRTM1 and SRTM3 datasets relative to ODP1 does not exceed 1.9 % on route segments ranging from 8.24 to 9.7 km in length, but may increase to 10.68 % on shorter segments

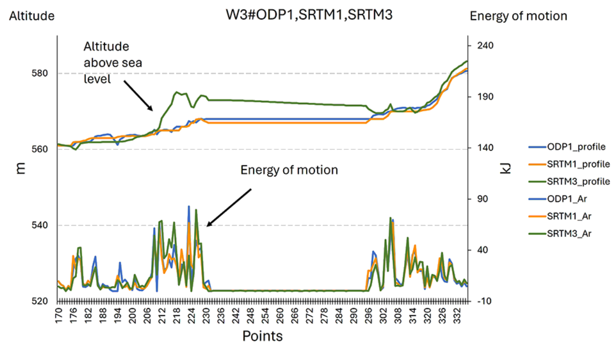

Fig. 13. Driving energy distribution along a segment of Way R3 for the ODP1, SRTM1, and SRTM3 datasets

(0.228–0.581 km) characterized by significant peak differences in elevation profile during uphill and downhill movement. The largest deviations in the topographic profile – and consequently the highest errors in driving energy calculation – are observed for the SRTM3 dataset, which is due to its lower resolution. SRTM1, while having a broader spatial coverage (compared to both SRTM3 and ODP1), spans nearly the entire land surface of the Earth. Considering the error level ranging from 0.908 to 3.387 % relative to ODP1 on both long and short route segments, SRTM1 can be considered sufficiently accurate for predicting driving energy consumption in the selected region.

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Вплив топологічних даних на прогнозування енергії руху електромобіля

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Мета. Оцінити вплив частоти дискретизації та джерела топографічних даних на точність розрахунку витрат енергії руху електромобіля із використанням стандартних протоколів випробувань.

Методика. У роботі здійснено розрахунок енергії руху електромобіля на основі теоретичної моделі, що враховує топографічний профіль маршруту й режим руху відповідно до обраного тестового протоколу. Аналіз проведено для кількох альтернативних шляхів одного маршруту європейськими дорогами за різних значень кроку дискретизації та джерел топографічних даних.

Результати. Встановлено, що частота дискретизації й точність топографічних даних суттєво впливають на результати розрахунку енергії руху. Визначено діапазон кроків дискретизації, що забезпечують прийнятну точність за умов зниженого обчислювального навантаження. Обчислені похибки для різних джерел даних залежно від характеру топографічного профілю маршруту.

Наукова новизна. Встановлена залежність точності розрахунку витрат енергії руху електромобіля від частоти дискретизації й обраного джерела топографічних даних з урахуванням рельєфу місцевості. Визначені граничні умови, за яких збільшення кроку дискретизації або використання менш точних баз не спричиняє суттєвих похибок.

Практична значимість. Отримані результати дозволяють обґрунтовано обирати оптимальний крок дискретизації та джерело топографічних даних для підвищення точності прогнозування енергоспоживання легкового електромобіля під час вибору маршруту.

Ключові слова: *електромобіль, планування маршруту, топологічний профіль, WLTP, дискретизація, топологічні бази*

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