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A statistical analysis of energy and power demand for the tractive purposes of an electric vehicle in urban traffic – an analysis of a short and long observation period

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Abstract. The article presents the results of a statistical dispersion analysis of an energy and power demand for tractive purposes of a battery electric vehicle. The authors compare data distribution for different values of an average speed in two approaches, namely a short and long period of observation. The short period of observation (generally around several hundred meters) results from a previously proposed macroscopic energy consumption model based on an average speed per road section. This approach yielded high values of standard deviation and coefficient of variation (the ratio between standard deviation and the mean) around 0.7-1.2. The long period of observation (about several kilometers long) is similar in length to standardized speed cycles used in testing a vehicle energy consumption and available range. The data were analysed to determine the impact of observation length on the energy and power demand variation. The analysis was based on a simulation of electric power and energy consumption performed with speed profiles data recorded in Poznan agglomeration.

1. Introduction

Nowadays attention is paid to minimizing fuel and energy consumption of vehicles. For battery electric vehicles the question of finding the route optimized for the lowest energy consumption is especially important due to their low range and the resulting range anxiety. Vehicle power and energy demand for tractive purposes depends on speed and resistance forces. The values of both these variables are random by nature and hence a wide dispersion is possible. They are affected by a random speed profile due to urban traffic nature caused by various interactions between vehicles in traffic, the infrastructure, driving style and traffic lights.

As the energy is an integral of a power history over time, and when the time is quite long, the variability of energy is much smaller than the variability of the value of instantaneous power demand. Due to random traffic conditions special standardized speed profiles are usually applied to estimate the average energy consumption for ICE and EV vehicles to enable comparison between various vehicles. Such standardized profiles simulate in laboratory conditions a type of driving in a city traffic and are several kilometers long.

The authors of this article previously suggested a macroscopic model for estimating the average power demand and energy consumption ("Tank-to-Wheel") over a short road section (several dozen meters to a hundred meters) based on the average speed of a vehicle over this road section [1]. The model was

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based on statistical data obtained from real speed data profiles and the microscopic energy consumption model calculated for short periods of time and distance traveled.

The fact that the same average speed value can result from different speed profiles poses w problem while building a model in this manner. It also influences the average power demand and average energy consumption values and one can find that the same average speed results on different levels of energy consumption (figure 1) or average power demand.

With this data it is possible to find equations with adequate parameter values to approximate these statistical data [2, 3]. If only aggregated statistical data is used, e.g. the average speed and average power demand or energy consumption, the models extrapolating this data may yield highly inaccurate results as it is difficult to comply with speed variation inside the observation period (in the case of traffic flow simulation: simulation step). Thus, due to this random nature of power demand and energy consumption data, questions arise if also power demand and energy consumption values variability can be taken into account. The authors assumed that it will be useful to consider an additional value (for example a standard deviation) to asses and model energy consumption with different levels of probability.

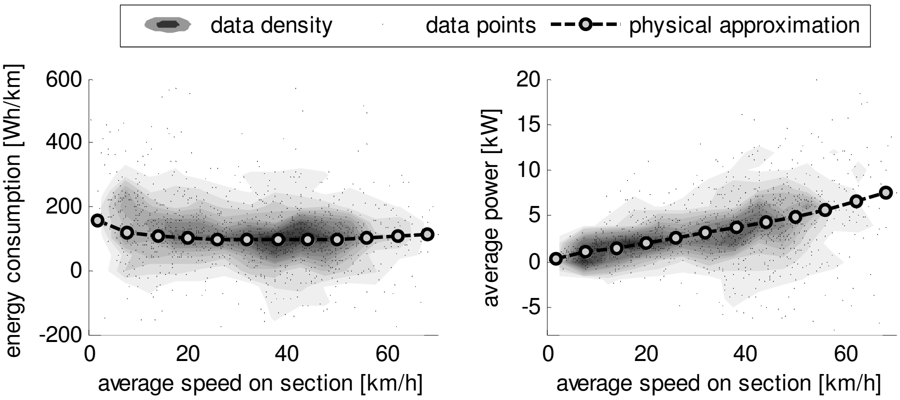

Figure 1. Specific energy consumption per route section calculated for speed profiles recorded in Poznan agglomeration.

2. Power and energy consumption data and models

The models the authors suggested in previous works were an approximation of the data presented in figure 1. The data of power demand and energy consumption was obtained with the simulation of Backward-Facing Model of longitudinal dynamics of battery electric vehicle Nissan LEAF with speed profiles recorded during everyday traffic used as an input. Speed profiles were recorded in Poznan agglomeration during normal, everyday driving performed by four drivers. The recording was carried out with a GPS receiver and data logger. Vehicle parameters were adjusted to represent the first generation of Nissan LEAF battery electric vehicle and energy consumption values observed during standardized tests [4, 5]and reported by users [6].

It is important to note that by energy consumption and power demand the authors mean the energy and power supplied from the battery to the inverter for traction purposes (Fig. 2).

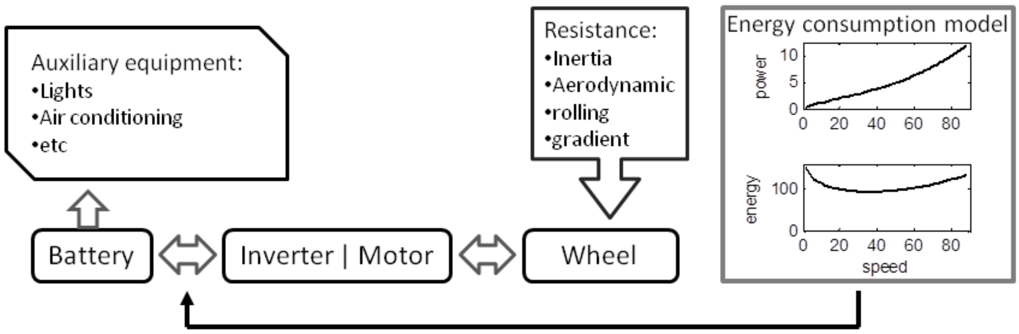

Figure 2. Flow of energy in a battery electric vehicle and a point of interest of this article supplemented with the presented model of energy consumption.

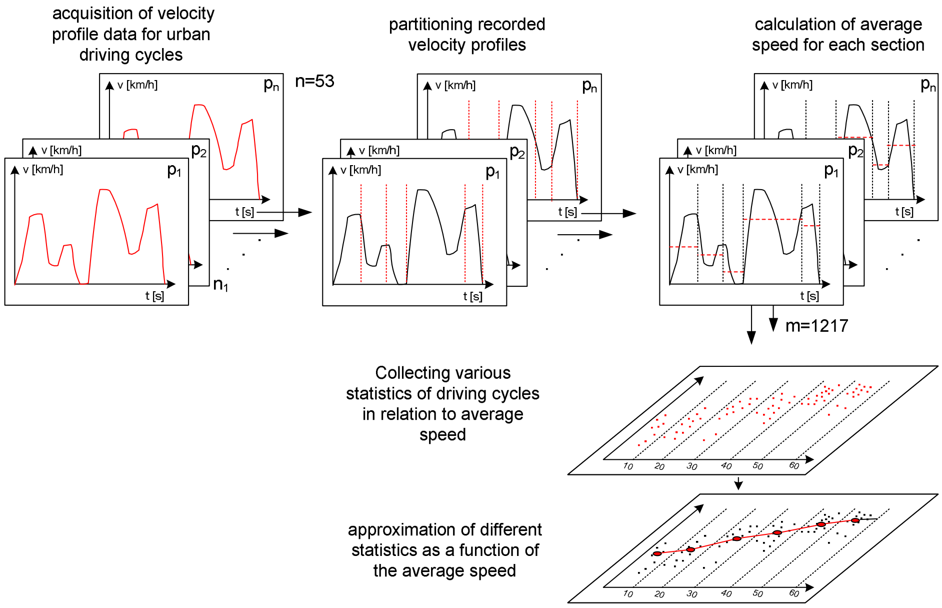

Figure 3. Driving cycle data processing procedure.

The following methodology was used to obtain the average energy consumption data in relation to average speed (Fig. 3):

a) power demand data and energy consumption data were modelled with a microscopic simulation of Backward-Facing Model [7]
b) the trips resulting in a several kilometers long speed, power and energy consumptions time histories were divided into much shorter route sections (links between nodes) adequately to time points at which the car was in a road network node (all junctions),
c) statistical parameters: the average speed, average acceleration and deceleration, average power, and energy consumption were automatically calculated for every section with specially programmed procedures in Matlab,
d) the average values obtained were ranked according to the speed intervals they belonged to, which were established with a constant width of 5 km/h from 0 to 70 km/h
e) for every average speed interval one mean average speed and mean average variable were calculated with the points of relationship between the average speed over the section and the average power demand and average energy consumption per unit distance
f) the obtained relationship for power demand was approximated with a function based on a sum of motion resistance:

$$P_{el} = \frac{P_{roll}+P_{aero}+P_{inertia}}{\mu} \quad (1)$$

where: P_{el} is electric power supplied from battery for tractive purposes, P_{roll} is rolling resistance power, P_{aero} is aerodynamic resistance power, $P_{inertia}$ is inertia resistance power and μ is battery to wheel efficiency of electric drive.

The user of this model then needs to know the average speed over every route section (link). Then it is possible to estimate the average power demand and later to calculate the energy used over the section by multiplying the average power demand and time spent in this section (fig. 4). It is a good method also to include the energy consumed by different auxiliaries. The consumed energy can also be calculated by multiplying energy consumption and the distance unit and the section distance.

The model obtained after the approximation is deterministic and predicts the energy consumption with 50% of probability that a real energy consumption will be lower than or equal to the one predicted. To provide tools to comply with higher values of probability the authors analyzed the energy consumption variability.

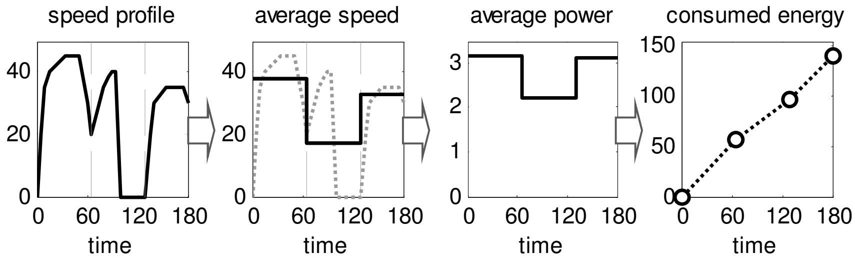

Figure 4. The idea of proposed macroscopic energy consumption model. Speed data are available only as average speed over section of road, based on this information average tractive power is estimated. Value of average power is multiplied by time spend on section to calculate energy consumed on this section.

2.1. Long and short observation period

As the nature of road infrastructure results in big differences in section (link) lengths, the authors decided to compare the average power demand and energy consumption per distance unit obtained from the whole trip analysis and from the proposed model.

2.1.1.Long observation period data.
In the article a long observation period was represented by the length of the whole trip. The average length of a single trip recorded in Poznan agglomeration was around 7 km, the shortest trip was only 1.44 km long, while the longest was 13.54 km long. The average number of sections per trip was 23.4, the lowest was 6, and the highest was 61. The mean average speed of all trips was 24.55 km/h, with a standard deviation of average speed equal 6.06 km/h.

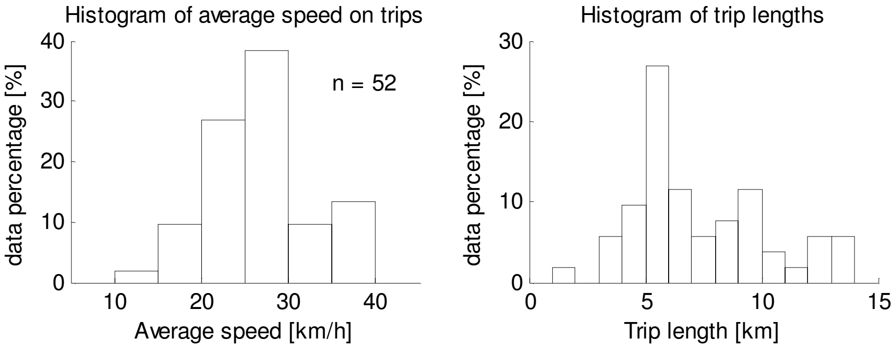

Figure 5. Composition of data with long observation period. Each bar represents data within speed interval 5 km/h wide, or trip length interval 1 km wide.

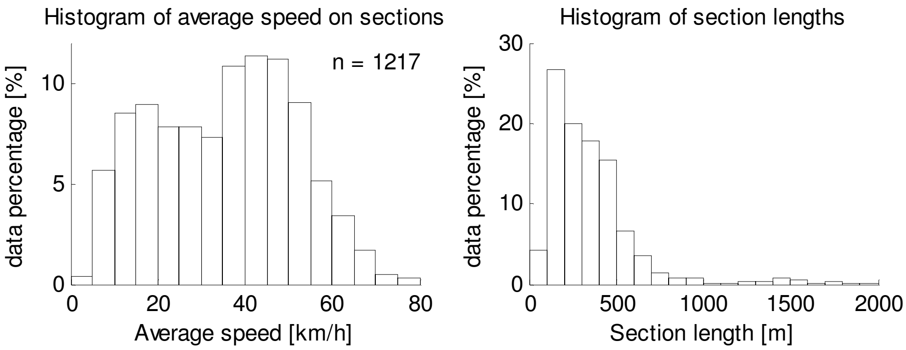

Figure 6. Composition of data with short observation period. Each bar represents data within speed interval 5 km/h wide, or trip length interval 100 m wide.

2.1.2.Short observation period data.
In this article a short period of observation is represented by the length of road section between two intersections. The average length was around 300 m and over 92% of section*s* were no longer that 600 m. The longest recorded section is slightly over 2.5 km long and the median length was 243 m. Over 30% of sections were shorter than 150 m.

The mean average speed of all sections was 32.7 km/h, with 84% of sections having average speed lower than 50 km/h (legal speed limit for urban areas in Poland).

2.2. Methodology of analysis and interpretation of chosen variables
Speed profiles gathered in Poznan agglomeration were used to calculate consumed energy and average power demand of electric vehicle using methodology presented in section 2 of this paper. The authors analysed the relationship between the average speed of vehicle over a short or long observation period and the average value of power demand or energy consumed in these periods. To analyse data for a short observation period for every section of the route the authors calculated statistical parameters of energy consumption per distance unit and average power demand. In the next step the obtained values were ranked according to average speed intervals they belonged to, established with a constant width of 5 km/h from 0 to 70 km/h. Then statistical parameters were calculated :

g) for every section:
- average value – was calculated as the mean value of the continuous variable ($f(t)$) over time (T):
- $$X_{avg} = \frac{1}{T}\int_0^T f(t)\,dt \quad (2)$$

h) standard deviation – was calculated with the formula:
- $$s = \left(\frac{1}{T}\int_0^T \left(f(t) - X_{avg}\right)^2 dt\ \right)^{\frac{1}{2}} \quad (3)$$

i) for every average speed interval:
j) mean value – was calculated as the arithmetic mean of a discrete number (N) of samples (x_i):
- $$X_{mean} = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (4)$$

k) standard deviation – was calculated using the formula:
$$s = \left(\frac{1}{N-1}\sum_{i=1}^{N}(x_i - X_{mean})^2\right)^{\frac{1}{2}} \quad (5)$$
l) Coefficient of variation (CV) – was calculated as a ratio of a standard deviation and the mean or average value. It allows to asses data dispersion. For normal distribution it means that:
m) 68,3, 95,4 or 99,7 % of probability that a sample value is between $mean(1 \pm CV), mean(1 \pm 2\ CV)$ or $mean(1 \pm 3\ CV)$ respectively.
- It also means an 84% or 98% probability that the sample value is lower than $mean(1 + CV)$ or $mean(1 + 2\ CV)$ respectively,

n) Cumulative Distribution Function (CDF) – a function describing probability that any data point (d_i) has value equal or lower than argument (x) of function:
$$CDF(x) = P(d_i \le x) \quad (6)$$
or it can be interpreted as a percentage of samples having value equal to or lower than x.

3. Results of analysis o statistical dispersion of power and energy variables

Calculated statistical parameters of average energy consumptions per unit distance and average power demand are presented in fig. 7. The level of a mean value of average energy consumptions per unit distance is similar in whole range of examined average speed, in contrast to increasing mean average power demand. Because of this the article mainly focuses on analysis of statistical dispersion of an average energy consumptions per unit distance, while the statistical dispersion of an average power demand was treated as supplementary data.

The values of standard deviation, both for the average energy consumption per unit distance and the average power demand - are quite high, almost equal to the mean value of the analysed variables. For average energy consumption per unit it is between 90 and 160 Wh/km, and for power demand the value rises linearly with speed, which results from power definition as the force multiplied by speed in the direction of the force.

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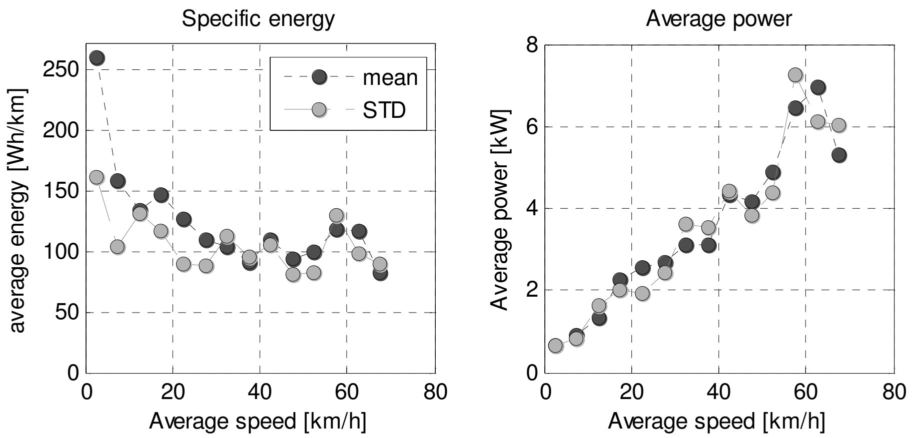

Figure 7. Mean value and standard deviation of average energy consumption per distance unit and average power relative to average speed on section.

3.1. Statistical dispersion of average speed and average energy consumption per distance unit

Statistical dispersion of the average energy consumption per distance unit for a short observation period is very high, with coefficient of variation values for individual speed intervals between 0.6 and 1.1, and the overall value of 0.91 - fig. 8. There is a slight inclination, probably resulting from decreasing mean values with rising speed. The variation coefficient of speed within a section falls from the top value of almost 2 to about 0,1 at speeds higher than 45 km/h.

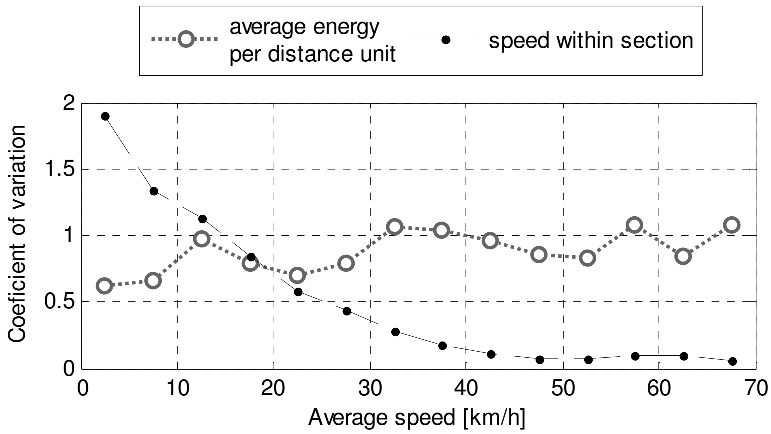

Figure 8. Coefficient of variation of average energy consumption per distance unit energy for short observation period data, supplemented with mean coefficient of variation of speed within section.

Contrary to preliminary hypothesis a statistical dispersion of the average energy consumption per distance unit and power demand (Fig. 10) does not decrease as the average speed increases despite a decreasing coefficient of speed variation on section (i.e. the mean variation -of speed inside an individual section, not the variation between data samples). A statistical dispersion of average energy consumption per distance unit for a long observation period is significantly smaller, with coefficient of variation around 0.15.

Figure 9. shows a significant disproportion between the distribution of data from individual sections and the data for whole trips. Due to the number of data points for individual sections, the distribution is shown by cumulative distribution function (CDF) values calculated for each speed interval.

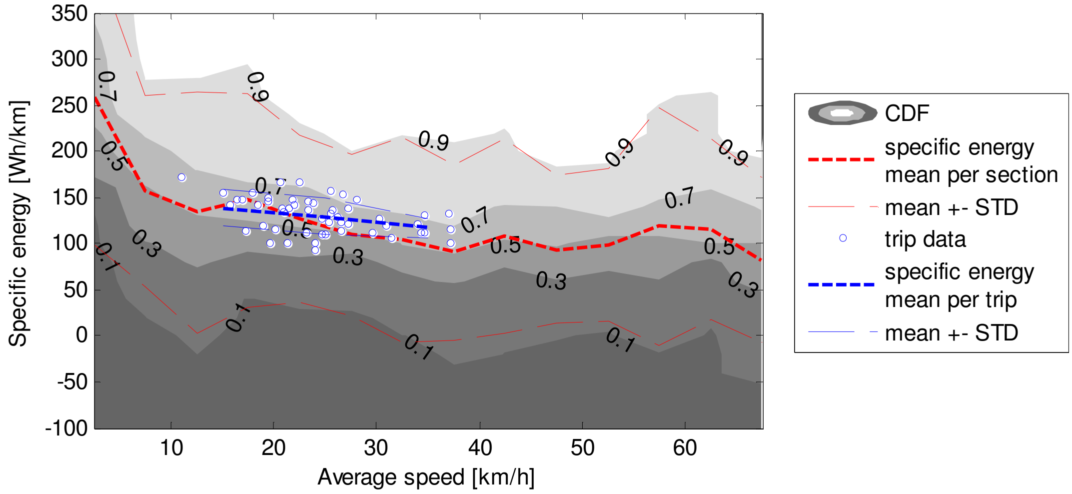

Figure 9. Mean average energy consumption per distance unit for short (red) and long observation period (blue). Graph is supplemented with visualisation of CDF of specific energy for short period of observation and data points from long period of observation.

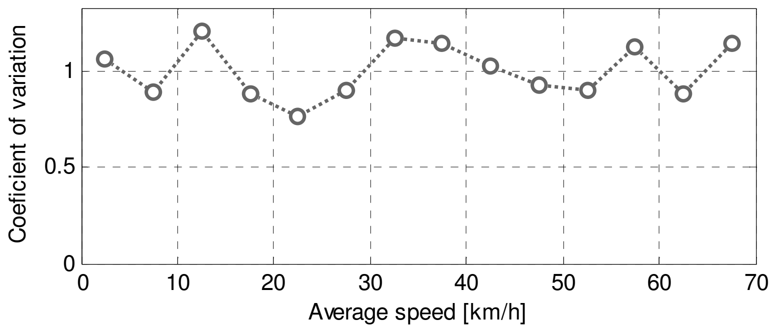

Figure 10. Coefficient of variation of average power depending on average speed.

A statistical dispersion of average power demand shows similar trends to the dispersion of average energy consumption per distance unit, but without a visible trend (increasing or decreasing) and with slightly higher values of coefficient of variation, ranging from 0.76 to 1.2.

3.2. Impact of section length on statistical dispersion of average energy consumption and average speed

As there was big difference observed between coefficients of variation for short and long periods of observations additional analysis was performed to examine the impact of section (link) length on statistical dispersion on calculated average energy consumption per distance unit. In order to perform this analysis all sections were ranked according to their lengths to analyze a section length frequency distribution. For a section length the constant interval width of 100 m was used from 0 to 700 m and over this value the width of length interval was increased to avoid creating data intervals with less than 13 samples (fig. 11).

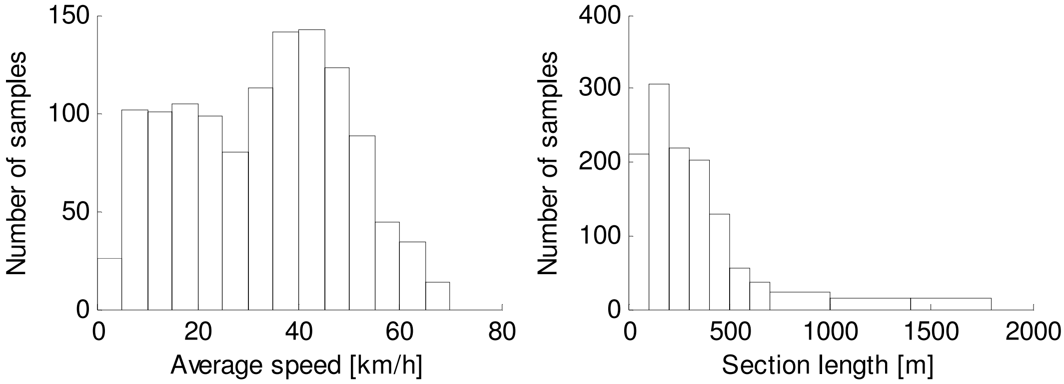

Figure 11. Average speed and section length intervals with sample count.

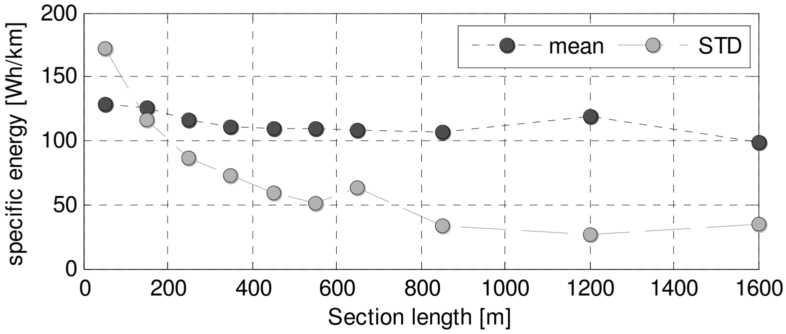

Figure 12. Mean value and standard deviation of specific energy relative to section length.

Mean of average energy consumption per distance unit calculated for length interval changes only slightly with the increasing section length, but the standard deviation noticeably decreases (Fig. 12). As a result, coefficient of variation of average energy consumption per distance unit decreases with the increasing section length (also period of observation)(Fig. 11), from value over 1.3 for sections shorter than 100 m to the lowest value of 0.22 for sections over 1 km long. The local peak of CV for the length of 600 m to 700 m may be the result of changes in average consumed energy relative to section length, which in turn results from the randomness of the collected data (more data could help to overcome this problem). CV of specific energy calculated for whole trips is around 0.15. For section lengths over 700 meters CV has a value over 0.3, but this could be the result of data scarcity and drop in the mean value of average energy.

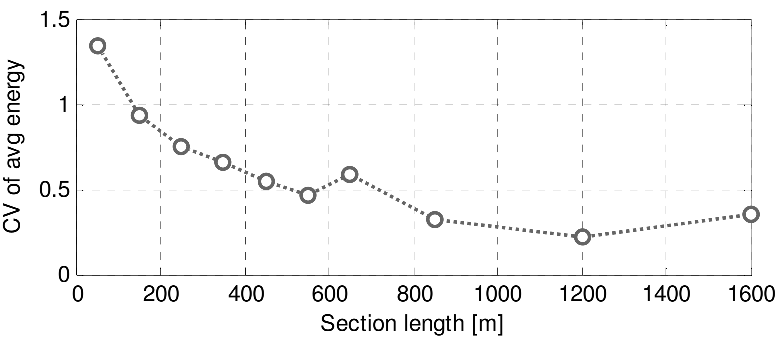

Figure 13. Coefficient of variation of specific energy

In order to test how CV of average energy consumption per distance unit behaves for longer periods of observation individual trips were merged to form routes with length over 20 km. The result was 15 trips with mean length of 24 km and CV of specific energy about 0.12. Aggregation to trips with length over 30 km resulted in only 10 trips with CV around 0.095.

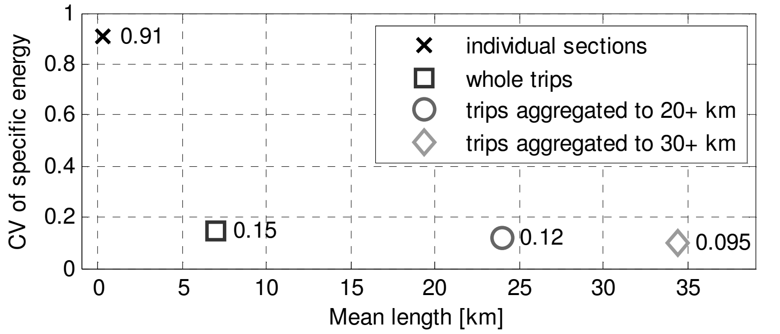

Figure 14. Coefficient of variation of specific energy for short and long period of observation.

In order to test how CV of specific energy behaves for much longer periods of observation the individual trips recorded were then merged to form routes over 20 km long. The result were 15 trips with the mean length of 24 km and CV of specific energy about 0.12. Aggregation to trips with length over 30 km resulted in only 10 trips with CV around 0.095 - figure. 13.

The graph in figure 13 shows the results of the analysis of the impact of the section length on average speed. This result shows that longer sections generate data with higher average speed, which can be associated with freer flow traffic (fewer obstacles and turns which slow down a vehicle). The standard deviation of average speed maintains a similar level regardless of the section length.

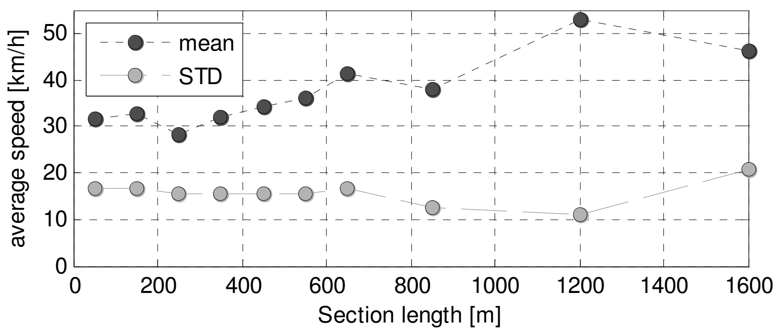

Figure 15. Impact of section length on average speed on section.

4. Summary

The concept of a model of average energy consumption for short sections was adopted because this method of representing roads infrastructure is used in traffic simulation software along with a similar way of obtaining and presenting data in on-line navigation systems. The model is expected to improve the accuracy of energy consumption predictions by using the average speed on each section data in comparison to the models based on the average speed for the whole route. However, an analysis of energy consumption distribution presented in the article indicates a high level of uncertainty for predictions for individual route sections based only on average speed information.

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The key findings from obtained results are:

– for short observation period a statistical dispersion of specific energy is roughly independent of average speed. With an increasing length of observation period data dispersion decreases.
– the value of coefficient of variation for energy consumption is higher than 0.4 for section lengths shorter than 700 m.
– while predicting energy consumption it means a high inaccuracy for individual route sections but with increasing travel length the accuracy will improve.

In future the authors will develop the statistical model which helps to aggregate energy consumption estimates from a number of sections and aggregate its uncertainty, thus enabling to obtain much lower values of it for the whole route.

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