Energy Consumption Analysis for Green Routing - Data Collection from Electric Vehicles

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***Abstract*—The current state in navigation and route calculations is mostly concentrated offering two route options for drivers: shortest and quickest route. With the environmental awareness and fuel prices raising the energy consumption of a route should be taken into consideration. The problem in finding the route consuming the least energy is not the lack of minimization algorithms but finding correct energy values for different parts of the path. This article introduces the equipment and methods for collecting the necessary data in an efficient manner, providing base values for route parts. It also presents examples, which can later be used for algorithm development.**

I. Introduction

Excessive energy consumption has consequences that are well know - inefficient utilization of energy resources leads to unnecessary local and global pollution, overall rise of costs and scarcity of energy where it would be needed. Traffic is one of the major domains where there is still much to do to improve energy efficiency. Gasoline and diesel powered vehicles produce a poor efficiency of 15-25%, whereas electric vehicles achieve as high as 60% efficiency [1]. Despite improvement in energy efficiency of the vehicles there still exists large potential for additional energy savings.

Navigation systems are generally well available for all the major urban areas and have become a part of our daily lives. At the moment navigation route selection is concentrated on two major approaches - the shortest and the quickest route. Some navigation systems also provide an option for avoiding road fees. The algorithms for finding the minimum length path are generally well known and well discussed in mathematics and operations research [2]–[4]. Data model for algorithms is simple. It consists of positive road lengths or times and speed limit information. Energy consumption is more multifaceted problem. The energy consumed between two points on the road is a product of car attributes, driver behavior and road attributes, including driving conditions [5]–[7]. With regeneration techniques in hybrid and electric vehicles some roads and streets (links) can also achieve negative energy consumption values, thus the driving direction must be also considered [8].

The motivation for driving technique improvements and route optimization seem to be of high value. Different eco-driving techniques are estimated to provide benefits up to 33 million metric tons of carbon dioxide saving and $7.5-15 billion in monetary savings [9]. These eco-driving techniques are for example eliminating stop-and-go driving and optimizing acceleration and speed of vehicle. Guo et al [10] present a different approach on fuel and emission saving in traffic by choosing the route based on road emission attributes. The study uses simulation examples in real urban environment where roads are given values based on i.e. traffic conditions and speed. Guo argues that intelligent route optimization can lead up to 27% CO^2 savings with rise of 11% in travel time for random drivers. The study also emphasizes the importance of target groups - most of the benefits in fuel and emission savings can be achieved without considerably longer travel times within a limited group.

On top of energy, emission and monetary savings energy optimal routes can also benefit the electric vehicle drivers who still suffer from insufficient battery capacity and thus so called range anxiety, the fear of not reaching the destination.

In this paper we introduces the equipment and methods to collect the necessary data in an efficient manner, providing base values for route parts. In addition, we present examples, which can later be used for algorithm development. The paper continues with evaluation of route energy consumption in Section II. Next, our measurement devices and methods are presented in Section III. In Section IV the results from the collected data are illustrated and Section V discusses about possible implications. Finally we conclude the paper in Section VI

II. Evaluating route energy consumption

When describing a transportation system it is commonly modeled as a graph network of nodes and links. Nodes are the points where roads intersect or the points of relevant change (i.e. changing speed limits). Links (e.g. roads) are the lines between the nodes. An illustration of two routes starting from A and finishing to X is given in Fig. 1. A,B,C,D and X are the nodes and lines between them present the links.

Links can be given values based on simple attributes (i.e. distance, speed limit) but some attributes need more data collecting (i.e. capacity utilization). The models also have two natures, static and dynamic. Road length (distance) is static information but the average speed of a car travelling can vary based on time of the day (rush hour) or weather conditions (rain).

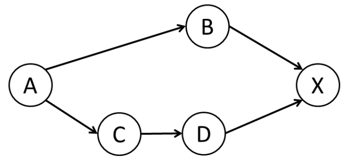

Fig. 1. Two routes from starting point A to destination X.

Table I presents the different factors affecting energy consumption while driving. Based on this table we can emphasize few important things. One, if we want to compare energy consumption of the road links, the effect of driver and car should be removed. Two, the energy value of a road link is not static, but dynamic. The value is changing based on several conditions i.e. driving speed or water on the road. Three, the energy value can differentiate radically when the driving direction is taken into account.

The table implicates difficulties. If we want to create an energy value for a road link we think immediately the vast amounts of data needed. The road should be driven with several cars, different drivers and in different driving conditions. This seems to lead to unacceptable spending of resources.

In the next chapter we present a methodology for collecting energy consumption data simultaneously with accurate speed and acceleration data as well as driver behaviour data in order to separate the drives, car and road effect of each other.

Total energy is the function of the above factors presented in Table I

$$\text{Total energy} = f(\text{driver}, \text{car}, \text{road}). \tag{1}$$

It would be beneficial to approximate this as

$$\text{Total energy} \approx f(\text{driver}) + f(\text{car}) + f(\text{road}). \tag{2}$$

III. Measurement equipment and modeling methods

There are few options for collecting data from vehicles while moving. One option valid for modern cars is to read the CAN bus information from the on-board diagnostics port (OBD) which provides fuel consumption readings. Collecting the data is fairly easy with low-cost data recording devices that can be easily bought or the data can be directly saved on PC hard drive. This method however comes with some disadvantages. The data sampling rate is fixed and given by car manufacturer. The data is also filtered in a way suitable for vehicle's internal utilization. Therefore the data from different car models is not commensurate and can not be used in generalizing information.

TABLE I. Different factors affecting energy consumption

Driver	Car	Road
Acceleration	Weight	Speed
Breaking	Drag co-efficient	Traffic
Lane changing	Tires	Stops
Passenger load	Drivetrain (i.e. motor and transmission efficiency)	Weather and temperature
		Potential energy (i.e. ascending or descending hill)

The other option for data collection is dedicated measurements with known sensors. This kind of plug-and-record measurement system allows to use different vehicles and the results are comparable. For these reasons a dedicated measurement was chosen. The choice of vehicle was not difficult. The electric vehicle can provide high accurate energy data with a high sampling rate and easier to install sensors compared to internal combustion engine. We used a 2007 Volkswagen Passat, which was converted to an all-electric vehicle. The vehicle has 24 kWh battery pack, 285 V nominal terminal voltage and maximum power output limited to 70 kW. The motor is a brushless DC motor and the converter is bidirectional enabling bidirectional power flow thus regenerative braking.

A. Energy measurement

The energy measurements were conducted directly from the EV battery terminals and high voltage cable. This allows measuring power consumption accurately with a high sampling rate. The current measurement was conducted with LEM HTFS-400P current transducer which provides galvanic separation, maximum current measuring range of ± 400 A (bi-directional for regenerative braking values) and output in form of voltage signals between 0-3 V. Current measurement accuracy was stated in the data sheet to be 1% and linearity as well as thermal condition effects were small. The reaction time for the transducer is measured in micro-seconds enabling a very high sampling rate if needed.

The voltage measurement took place directly from the battery terminals. The voltage message was lowered by voltage division (1:11) to meet the 10 bit analog-to-digital converter maximum input voltage of 3 V. Fig. 2 illustrates the energy measurement setup. Sampling frequency was chosen to be 2 Hz in order to keep the amount of data on reasonable level in the testing phase. Sampling frequency for current and voltage is limited only by the analog-to-digital (AD) converter, which is in kilohertz scale. Measurement data was collected and transferred by Wapice WRM247 remote management system and stored to web server data base through GPRS connection.

With the current and voltage measurement we can calculate the energy consumption W within a time period t as

$$W(t) = \int P\,dt \approx \sum P\Delta t = \sum UI\Delta t, \tag{3}$$

where P is power, U is voltage, I is current and Δt is discrete sampling interval.

B. Location and motion measurements

To get location measurements, we used NovAtel DL-4+ dual frequency DGPS receiver. The GPS antenna was mounted on the roof rack during tests.Accuracy of this receiver is tens of centimeters in differential GPS mode, which makes it suitable for reference position. In addition, it provides speed information with high accuracy.

Wireless Xsens MTw trackers were used to collect acceleration and barometric data. These sensors also collected gyroscope and magnetometer data, however, those measurements were not used in our current system. Four Xsens MTws were mounted with the different locations on the vehicle; brake pedal, throttle pedal, steering wheel and as a master device

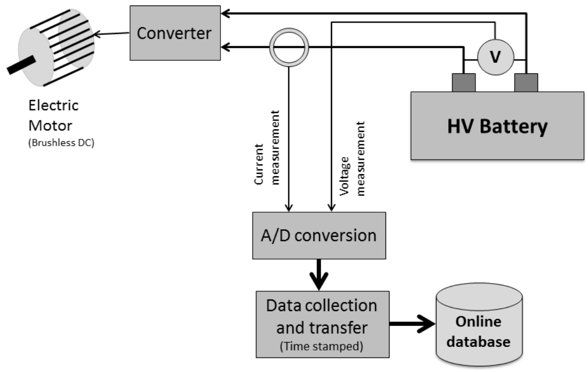

Fig. 2. Energy measurement setting

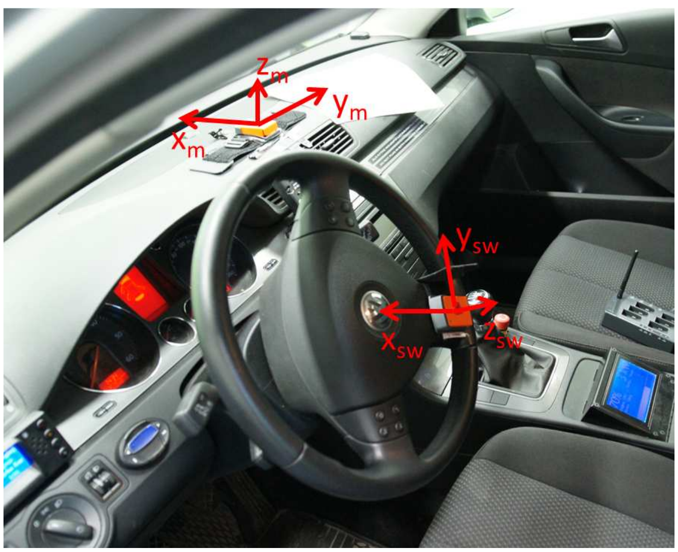

Fig. 3. Accelerometers attached to the steering wheel and dashboard

inside a car (sensors axes were parallel to vehicles longitudinal and lateral axis).

To make GPS and acceleration data comparable, the time synchronization between XSens MTws and DGPS receiver was done manually offline. By using the acceleration data we can get valuable information from the driving style and possibly remove or filter out driver effect from the energy consumption. This can be done, for example, by monitoring throttle position and longitudinal accelerations. Barometer provides information as a barometric altimeter and thus, for example, up and down hills can be tracked [11].

C. Steering wheel and pedal positions

To measure the orientation of the steering wheel or pedal accelerometers can be used as follows. The accelerometer mounted in coordinate frame m measures [12]

$$\mathbf{y}^m = \mathbf{a}^m - \mathbf{g}^m, \tag{4}$$

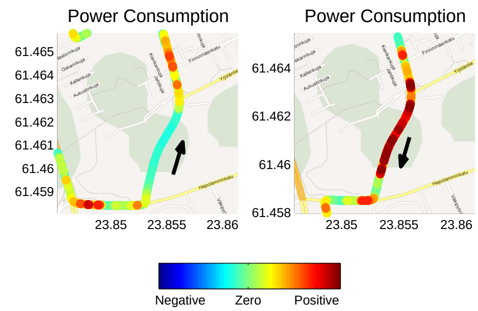

Fig. 4. Power consumption with different driving direction on the same route.

where $\mathbf{a}^m$ is acceleration and $\mathbf{g}^m$ gravity vector. Similarly the measurement from the frame sw is

$$\mathbf{y}^{sw} = \mathbf{a}^{sw} - \mathbf{g}^{sw}. \tag{5}$$

Assuming that the frames sw and m experience the same accelerations

$$\mathbf{y}^m = C^m_{sw}\mathbf{y}^{sw} + n. \tag{6}$$

wherein C^m_{sw} is unknown direction cosine matrix (DCM) to be solved. This can be done for example by minimizing

$$\underset{C^m_{sw}}{\operatorname{argmin}} ||\mathbf{y}^{sw} - C^m_{sw}\mathbf{y}^m||. \tag{7}$$

If we neglect the external accelerations ($\mathbf{a}$), the simplified version for the steering wheel can be used:

$$\alpha = \arctan\frac{y^{\text{sw}}}{x^{\text{sw}} + z^{\text{sw}}}. \tag{8}$$

Here α is the steering angle and x_{sw}, y_{sw}, z_{sw} are the steering wheel accelerometer readings from each axis. Before the estimation, it is advisable to use low pass or Kalman filtering to remove unwanted high frequency disturbances from the accelerometer data.

In our tests the master accelerometer unit was mounted to the vehicle (m frame) so that the x-axis was parallel to the longitudinal axis and y-axis parallel to the lateral axis. The master device along with the mounted steering wheel measurement unit (sw frame) are illustrated in Fig. 3.

To estimate orientation of the pedals (throttle and brake) we can use similar approach as presented above for the steering wheel. When the pedal is not pressed the angle of the pedal is defined to be zero and the angle increases as the pedal is pressed. It should be noted that if we use also the angular velocity information from the gyros, the more accurate steering wheel and pedal position estimation can be achieved. However, the accuracy provided by the accelerometers should be enough for system presented in this paper.

IV. RESULTS

To illustrate the effectiveness of our data collection system for green routing an example data set was collected. The results show that when selecting the the most energy efficient route,

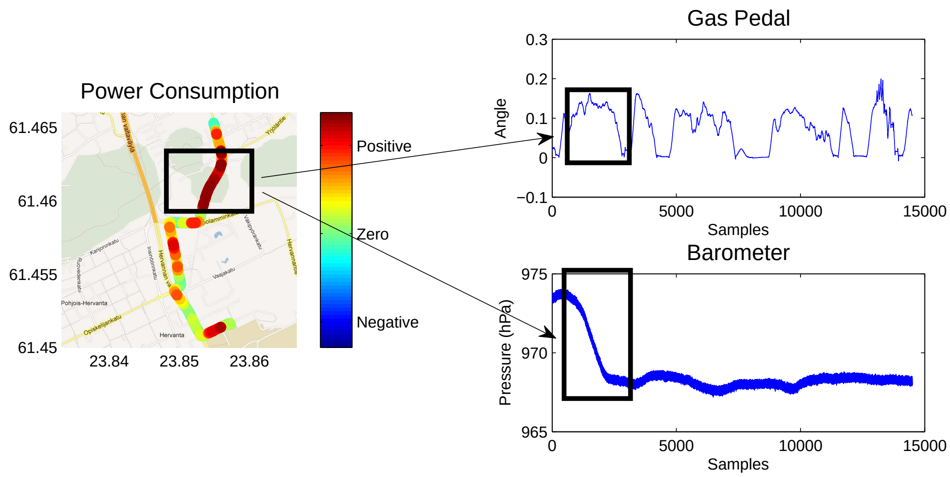

Fig. 5. Power consumption consumption on up hill

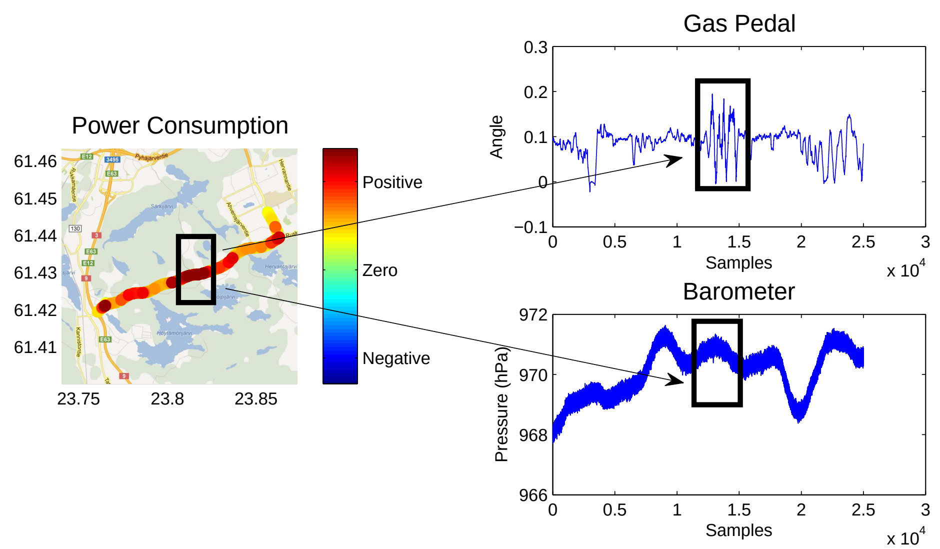

Fig. 6. Power consumption while pumping the throttle

the driving direction can have a large impact on energy consumption. As an example Fig.4 presents energy consumption on the same road link but to the opposite driving direction. In the figure, red color illustrates high energy consumption and blue color indicates regenerative energy. In this specific example the drastic difference in energy consumption is due to a large hill. In our measurement system the information from the direction of driving can be easily obtained from the collected data.

To demonstrate how the collected sensory data can be used to divide between different factors two example figures are shown. Figs. 5 and 6 show the energy consumption during the two specific locations during the test ride. The left hand side figure shows the power consumption and the right hand side figures present the position of the throttle pedal (up) and the measured pressure (bottom). In both figures we can see that inside the black boxes the energy consumption is very high. Nevertheless, the reason for the high consumption can be found from different factors. In Fig. 5 we can clearly see high change in the barometric data, pressure decreases dramatically which indicate uphill. Thus, the high energy consumption is due to *road* factors from Table I. However, in Fig. 6 there is not significant gradients in barometric data during the high consumption area, despite we can see pumping effect on the gas pedal position. Thus, the reason here can be categorized to *driver* factors.

V. Discussion

In summary, these results have several implications. One, the devices created for electric vehicle measurements provide accurate, real time data that can be stored and used later for analysis. Two, with the information provided by the equipment can be used in (urban) traffic planning and driver information systems. It can be also used in evaluating the energy cost of transportation. More sophisticated energy data from electric vehicles could also be used to create better predictions of intra-day power need for EV charging infrastructure compared to existing ones [13].

In addition, the system can be used to make the analysis of energy consumption in making intra-day the predictions of electric power and energy demand. It would be also possible to use same measurement system to teach good driving behavior and explain the root causes of poor driving behavior. However, this would arguably require a longer usage of the mounted measurement system.

VI. Conclusions

Choosing the energy efficient route, also called green routing, is a subject of great interest enabling emission and monetary savings. The link to create a model of green routes and energy consumption on different road links is still in its beginning. It has been shown that the simple measures (i.e. travel distance) do not always correlate with energy consumption. That is why a novel, more accurate method for collecting the necessary data is needed. The equipment, methods and fundaments that are needed when collecting the data were introduced. These findings enable data collection for finding the weight values to different road links. The measurements were conducted with equipment that are easily transferable to different vehicles.

As a result of measurement experiences we can conclude that electric vehicles provide an excellent platform for collecting data for transportation and route planning needs. Electric vehicles energy consumption can be accurately, easily and reliably measured and later compared with other vehicles. It can also be utilized in creating better models where driver behavior, vehicle attributes and road conditions can be separated. When the road link values are based on real measurements and are complemented with external weather and traffic data a green routing service can be created for all car users with normal smart phones, without the need for high accuracy sensors or special devices.

The advantages that EVs and dedicated measurements provide seem clear. The OBD data collection demands huge amounts of driving cycles to generate sufficient information. This calls for unnecessary waste of resources.

In the near future more data collecting is needed to generate a holistic picture of the traffic network. Also, the mathematical models based on the collected data must be validated with test to see what is the true accuracy.

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