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Battery electric vehicle energy consumption prediction for a trip based on route information

Jiquan Wang¹,², Igo Besselink² and Henk Nijmeijer²

Abstract
Drivers of battery electric vehicles (BEVs) require an accurate and reliable energy consumption prediction along a chosen route to reduce range anxiety. The energy consumption for a future trip depends on a number of factors such as driving behavior, road topography information, weather conditions and traffic situation. This paper discusses an algorithm to predict the energy consumption for a future trip considering these influencing factors. The route information is obtained from OpenStreetMap and Shuttle Radar Topography Mission. The algorithm consists of an offline algorithm and an online algorithm. The offline algorithm is designed to provide information for the driver to make future driving plans, which provides a nominal energy consumption value and an energy consumption range before a trip begins. The online algorithm is designed to adjust the energy consumption prediction result based on current driving, which includes a vehicle parameter estimation algorithm and a driving behavior correction algorithm. The energy consumption prediction algorithm is verified by 30 driving tests, including city, rural, highway and hilly driving. A comparison shows that the measured energy consumption of all trips is within the energy consumption range provided by the offline algorithm and most of the differences between the measurement and nominal prediction are smaller than 10%. The offline prediction is used as a starting point and is corrected by the online algorithm during driving. The mean absolute percentage error between the measured energy consumption value and online prediction result of all trips is within 5%.

Keywords
Battery electric vehicle, energy consumption prediction, route information, driving behavior, online estimation

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Introduction
Battery electric vehicles (BEVs) are increasingly receiving attention because of the focus on environmental issues and usage of renewable energy. EVs have advantages in energy costs and local emissions compared to internal combustion engine (ICE) vehicles. However, the acceptance of BEVs is limited by a high purchase price, long charging time, few charging stations and limited driving range. The limited driving range and long charging time can make drivers more concerned as to whether they can reach the destination based on the current battery state of charge; this is called range anxiety.¹ Range anxiety is considered as one of the major factors that affects the acceptance of BEVs.

Apart from a bigger battery capacity and more charging facilities, an accurate energy consumption prediction along a chosen route before the start of the trip is also necessary to reduce range anxiety. Even though the battery technology is improving day by day, it is nevertheless expected that the battery capacity of mass adopted BEVs will still be constrained by weight and cost issues, so an accurate energy consumption prediction will remain an important topic. Studies on energy consumption prediction or remaining driving range prediction of BEVs can be mainly divided into predicting the future driving speed,²–⁸ modelling the energy consumption⁹–¹² and online prediction of the energy consumption based on a regression analysis.⁹,¹⁰,¹³

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Driving speed is one of the most important factors that can influence the energy consumption. There are basically three methods to predict the future driving speed: the first method is based on driving pattern recognition\textsuperscript{2,3,14}, the second method is to design a new driving cycle based on the statistical evaluation of real driving tests\textsuperscript{4,5} and the third method is to generate the future driving speed based on the trip information.\textsuperscript{8} However, the first two methods only consider the current speed recording and driving distance of this trip without considering the future road type. The third method can be applied together with the first or second method to increase the prediction accuracy, but it doesn’t take the individual driving behavior and real-time traffic information into consideration. Taking advantage of a modern navigation system, the road topography and even real-time traffic information can be obtained.\textsuperscript{6,7,15} The real-time traffic information can help to improve the speed prediction accuracy, but it is not currently available for every road segment.

The variation in driving behavior may result in a different energy consumption for the same route. The influence of driving behavior on the vehicle energy consumption can be quantified\textsuperscript{16} and the driving behavior can be modelled.\textsuperscript{3,17,18} However, the driving behavior is influenced by external circumstances,\textsuperscript{19} so a large amount of data is needed to model the driving behavior of one driver for different traffic intensities.

Mainly two kinds of energy consumption model are built to predict the energy consumption: regression models from real-world measurement\textsuperscript{10,12} or simple physical models with constant vehicle parameters.\textsuperscript{9,11,13,20} These models can predict the energy consumption accurately for a specific driving route and weather condition. However, the calculation accuracy will decrease if the driving route or weather conditions are changing.\textsuperscript{21–23}

The conventional approach of the onboard energy consumption prediction employed by car manufacturers is based on the projection of the past average vehicle energy efficiency.\textsuperscript{27} It is often perceived to be inaccurate due to lack of considering the future route and ambient conditions. Researches on energy consumption prediction tend to take the ambient temperature and driving route into consideration to improve the nominal energy consumption prediction accuracy during driving.\textsuperscript{28}

The main contribution of this paper is taking the influence of route information, weather conditions and driving behavior into consideration to predict the energy consumption. The energy consumption prediction algorithm presented here includes an offline and an online algorithm. The offline algorithm provides an energy consumption prediction result before a trip begins, which can give the driver a first impression on whether the vehicle can arrive at the destination or which speed to select to reach the destination. To consider the energy consumption difference caused by different driving styles, three energy consumption values are calculated: a maximum value, a minimum value and a nominal value. The online algorithm includes a parameter estimation algorithm and a driving behavior correction algorithm. The parameter estimation algorithm estimates vehicle parameters during driving, namely vehicle mass and rolling resistance. The driving behavior correction algorithm adjusts the energy consumption prediction result based on the current driving behavior and future route information.

This research is illustrated using an electric vehicle: the TU/e Lupo EL. It is built by the Dynamics and Control group of the Eindhoven University of Technology using a VW Lupo 3L as a donor vehicle, and “EL” is the abbreviation of “Electric Lightweight.”\textsuperscript{29} This paper is organized as follows. In the second section the software to obtain the road topography information is introduced. The offline algorithm is discussed in the third section. In the following section, the online algorithm is discussed. Then the offline and online algorithms are evaluated by driving tests on the public road. Finally, conclusions are given and suggestions for future work are introduced.

Road information

The vehicle energy consumption is influenced by the road topography information, including road type, traffic lights, speed limit signs and elevation data. The route information needs to be identified to provide an accurate energy consumption prediction, which is obtained from OpenStreetMap (OSM) and Shuttle Radar Topography Mission (SRTM).

OSM is a collaboration project to create a free editable map of the world that provides geographical data to anyone. It is created by volunteers performing systematic ground surveys with a handheld global positioning system (GPS) receiver. The data availability of OSM still varies from country to country, but the worldwide coverage is improving day by day.\textsuperscript{30} The OSM database is recorded in XML format, which shows all of the attributes for a line (roads, streets, paths) or a point of interest (POI).

SRTM is an international project spearheaded by the US National Geospatial-Intelligence Agency (NGA) and the US National Aeronautics and Space Administration (NASA). The objective of this project is to obtain digital elevation data on a near-global scale from 56° south to 60° north latitude, which comprises almost 80% of earths total landmass.\textsuperscript{31} The data have been released with a horizontal resolution of 1 arcsecond (30 m) globally since late 2014. The elevation information of a route can be obtained from the SRTM, using the route geographic coordinates.

Offline energy consumption prediction algorithm

In order to provide a base for the driver to make a future driving plan, the offline energy consumption
The offline energy prediction algorithm should give an estimate on the energy consumption before a trip begins. The energy consumption for a future trip is determined by driving speed, road information, weather condition and vehicle parameters. The structure of the offline energy prediction algorithm is depicted in Figure 1.

The route information and weather condition can be obtained before a trip begins. Route information is obtained from OSM and SRTM. The weather condition, including temperature, humidity, air pressure and wind speed and direction, can be obtained from a weather website. The influence of ambient temperature will be discussed in the section ‘Ambient temperature influence’. The wind direction can be easily changed by buildings, this leads to unpredictable result in a city environment. It is, however, suitable for highway driving, where the wind direction is stable and the contribution is large.

The driving speed is dependent on route information, traffic flow and driving behavior, where the last two cannot be predicted accurately beforehand. The driving behavior can significantly influence the energy consumption, experiments show that eco-driving can save energy consumption up to 50% for the same route compared to aggressive driving. Therefore, not only a “nominal driving speed,” but also two other driving speeds profiles are calculated by the algorithm: the maximum speed and the most efficient speed. For these three speed profiles the energy consumption is calculated, resulting in the nominal, maximum and minimum energy consumption.

For each type of road, the nominal speed has the highest probability. The most efficient speed is the speed which leads to a minimum energy consumption per kilometer. The most efficient speed of the Lupo EL is about 25 km/h, this value will even decrease when considering the influence of frequent start-and-stop driving in the city. Because the driver has to follow the traffic flow, she/he cannot drive at the most efficient speed on some roads, e.g. secondary road and primary road. In these cases, the most efficient speed is set to the minimum driving speed. If a serious traffic jam occurs during the trip, the energy consumption may increase beyond the maximum value. Since the real-time traffic information is not available for all roads, traffic jams are not considered in the offline algorithm, hence the maximum energy consumption is obtained for the maximum driving speed. The methodology to obtain the driving speed is discussed in the section ‘Driving speed profile’.

Ambient temperature influence

The ambient temperature will influence the vehicle rolling resistance, air density and auxiliary energy usage, e.g. interior heating or air conditioning. The usage of auxiliary systems can be measured directly during driving. The air density is a function of air pressure, relative humidity and ambient temperature. The humidity has a minor influence on the air density at higher temperature. According to the equations published in reference, the air density as a function of ambient temperature and pressure is shown in Figure 2, when the humidity is 80%.

The rolling resistance coefficient $f_r$ can be obtained through a coasting down test. Several coasting down tests have been done with the TU/e Lupo EL on various road types and for different ambient temperatures. The results are shown in Figure 3, and this figure also includes results from tyre manufacturer Michelin. It can be seen that the trend of rolling resistance coefficient $f_r$ with the ambient temperature are similar between our measurements and Michelin research. The increase of $f_r$ is about 30% when the ambient temperature drops from 30°C to 0°C. The influence of the road surface type on the rolling resistance coefficient $f_r$ is even more important compared to the ambient temperature. The dependency of $f_r$ on various road surfaces is estimated based on these measurements and listed in Table 1.

Figure 1. The demonstration of the offline energy consumption prediction algorithm. OSM: OpenStreetMap; SRTM: Shuttle Radar Topography Mission.

Figure 2. Air density as a function of ambient temperature and air pressure.
Driving speed profile

The driving speed profiles are predicted based on the OSM information, including road types, speed limit signs, road curvature and traffic lights. The initial value for the driving speed is based on the road type information, and then speed limit signs, road curvature and traffic light information will be used to adapt the speed profile.

Road type. There is a recommended driving speed range for each type of road, which is accepted by the public normally. For most road types, the driving speed is limited legally. Therefore, the first estimate of the driving speed profile is based on the road type.

Next, the speed profile is modified based on a statistical analysis of speeds from driving tests on the public road. Recordings of 700 km of driving are analyzed, the speed data are sampled for every meter driven. The distribution histogram of driving speed for each road type is shown in Figure 4. The black line in the figure is the curve fit of the distribution, which is obtained by the kernel density method and represents the most probable distribution. It should be pointed out that these driving tests were not done in the rush hour and no traffic jam occurred. Combining the statistical analysis result and legal speed limit for each road type, the maximum, minimum and nominal driving speed on each road type in the Netherlands is listed in Table 1.25

Table 1. Speed and rolling resistance data for various roads.

<table>
<thead>
<tr>
<th>Road type</th>
<th>Maximum speed [km/h]</th>
<th>Minimum speed [km/h]</th>
<th>Nominal speed [km/h]</th>
<th>Rolling resistance scaling</th>
</tr>
</thead>
<tbody>
<tr>
<td>Living street</td>
<td>15</td>
<td>5</td>
<td>10</td>
<td>1.40</td>
</tr>
<tr>
<td>Residential</td>
<td>30</td>
<td>10</td>
<td>20</td>
<td>1.25</td>
</tr>
<tr>
<td>Service</td>
<td>30</td>
<td>10</td>
<td>20</td>
<td>1.40</td>
</tr>
<tr>
<td>Track</td>
<td>30</td>
<td>10</td>
<td>20</td>
<td>1.40</td>
</tr>
<tr>
<td>Unclassified</td>
<td>50</td>
<td>20</td>
<td>25</td>
<td>1.25</td>
</tr>
<tr>
<td>Tertiary</td>
<td>50</td>
<td>25</td>
<td>35</td>
<td>1.20</td>
</tr>
<tr>
<td>Secondary</td>
<td>70</td>
<td>40</td>
<td>50</td>
<td>1.15</td>
</tr>
<tr>
<td>Primary</td>
<td>80</td>
<td>50</td>
<td>65</td>
<td>1.05</td>
</tr>
<tr>
<td>Trunk</td>
<td>100</td>
<td>70</td>
<td>80</td>
<td>1.00</td>
</tr>
<tr>
<td>Motorway</td>
<td>120</td>
<td>80</td>
<td>100</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Note: the road type is defined by OpenStreetMap (OSM); the tertiary road connects minor streets to more major roads, which is within large settlements for roads connecting local centres; the unclassified road is a minor public road typically at the lowest level of the interconnecting grid network, which has lower importance than the tertiary road.

Figure 3. The rolling resistance coefficient on various roads at different ambient temperatures.

Figure 4. The driving speed distribution on different types of road.25

Speed limit signs and traffic lights. The vehicle driving speed is influenced by speed limit signs and traffic lights. The speed limit sign is used in most countries to set the maximum speed, or minimum in some cases. The influence of a traffic light has also to be considered, because the vehicle may have to stop and wait.
However, the status of traffic lights cannot be predicted beforehand. To include the influence of traffic lights, half of traffic lights are assumed to be red, and the waiting time is estimated to be 30 s.

The speed limit sign and traffic lights are available as node information in OSM database. The position of the speed limit signs and traffic lights can be obtained once the travelling route has been determined.

Road curvature. If necessary a driver will slow down the vehicle before a corner to guarantee safe and comfortable cornering. The cornering speed is limited by the vehicle lateral acceleration and the relationship between the forward velocity \( v \) and the lateral acceleration \( a_y \) is given as

\[
a_y = \frac{v^2}{R}
\]

where \( R \) is the corner radius.

The lateral acceleration can reach approximately 8 m/s^2 on a standard vehicle during testing; however, it is limited to 3 m/s^2 in most cases for daily driving according to Lupo EL measurements. Therefore, the maximum lateral acceleration is taken as 3 m/s^2 in this research. When necessary the vehicle speed \( v \) is reduced in corners so that the lateral acceleration doesn’t exceed 3 m/s^2. The corner radius can be calculated based on the geographical coordinates of nodes available within OSM.

Acceleration/deceleration

The speed profile determined by road types, speed limit signs, road curvature and traffic lights is shown in Figure 5(a). It can be seen that this speed profile is discontinuous. The driver has to follow the traffic rules and drives smoothly, thus the vehicle has to slow down in a corner or in front of a traffic light. To obtain a realistic driving speed, the discontinuities between two target speed values should be connected by vehicle acceleration or deceleration, as the dashed line in Figure 5(b) shows.

The maximum acceleration and deceleration of the Lupo EL, determined by a one-pedal-driving control strategy is shown in Figure 6. The maximum acceleration is limited by the motor power of 50 kW at high speeds, whereas at low speeds the maximum acceleration is 4.6 m/s^2. The deceleration caused by regenerative braking is limited by the motor power of 24 kW at high speeds, and its value is \(-2\) m/s^2 at low speeds. According to measurements, the acceleration is smaller than 3 m/s^2 during normal driving. To take the influence of driving behavior into consideration, the maximum speed profile is assumed to be driven by an aggressive driver with a maximum acceleration of 4 m/s^2 and a maximum deceleration of \(-3\) m/s^2 at low speed. The nominal speed profile is obtained for normal driving with a maximum acceleration of 3 m/s^2 and a maximum deceleration of \(-2\) m/s^2 at low speeds. The minimum speed profile is driven by an eco-driver with a maximum acceleration of 2 m/s^2 and a maximum deceleration of \(-1.5\) m/s^2 at low speeds. The maximum acceleration and deceleration at high speed are all limited by the vehicle powertrain settings.

The acceleration or deceleration applied during the transition is determined by the driver and traffic situation. However, to simplify the calculations, the applied transitional acceleration or deceleration is determined by the difference between the current driving speed and target speed in this paper. If the difference is larger than 10 km/h, the maximum acceleration or deceleration is adopted, or else the applied acceleration linearly decreases from the maximum value to zero with the speed difference. It should be mentioned that the adoption of the maximum acceleration and deceleration is estimated based on the measurements from the Lupo EL. More statistical analysis needs to be done to determine the maximum and transitional acceleration and deceleration for different driving behaviors in future research.

Energy consumption model

The energy consumption model of the Lupo EL adopted here is a physical model, which is based on
vehicle longitudinal dynamics. The model is built in a reverse way, it can calculate the energy consumption for a given speed profile. The battery output power $P_{bat}$ is given as

$$P_{bat} = (F_r + F_{aero} + F_g + F_m)v + P_{pt,loss} + P_{aux}$$  \hspace{1cm} (2)$$

where $v$ is the vehicle speed; $P_{pt,loss}$ is the vehicle power-train loss, which is determined in a dynamometer test; $P_{aux}$ is the auxiliary power usage. The rolling resistance force $F_r$ equals

$$F_r = f_r m g \cos(\alpha)$$  \hspace{1cm} (3)$$

where $f_r$ is the rolling resistance coefficient, which is obtained in terms of the ambient temperature and road surface as illustrated by Figure 3; $m$ is the vehicle mass and the value is 1250 kg; $g$ is the gravitational constant, equals to 9.81 m/s$^2$ and $\alpha$ is the road slope. The aerodynamic drag force $F_{aero}$ is given by

$$F_{aero} = \frac{1}{2} \rho C_d A_f (v - W)^2$$  \hspace{1cm} (4)$$

where $\rho$ is the air density; $A_f$ is the vehicle frontal area, the value is 1.97 m$^2$; $C_d$ is the aerodynamic drag coefficient which equals 0.3 and $W$ is the wind speed in the driving direction. The force originating from the road slope $F_g$ is

$$F_g = m g \sin(\alpha)$$  \hspace{1cm} (5)$$

The acceleration force $F_m$ is given by

$$F_m = \left(m + \frac{4 J_w}{r^2} + \frac{J_m g}{r^2}\right) a_x$$  \hspace{1cm} (6)$$

where $J_w$ is the wheel inertia and equal to 0.75 kgm$^2$; $J_m$ is the motor inertia and equal to 0.0384 kgm$^2$; $r$ is the tyre radius and equal to 0.278 m; $g$ is the gearbox ratio and equal to 8.654 and $a_x$ is the longitudinal vehicle acceleration.

This model is verified by driving tests on the public road under difference circumstance, the results show that it can calculate the energy consumption with an error smaller than 5\%.\textsuperscript{25}

### Experimental results

In total 30 driving tests are done to evaluate the offline algorithm. In this subsection, a highway driving test is used to illustrate how the offline algorithm works. This specific test was done on July 6th 2015 between Eindhoven and Heel in the Netherlands. The driving route is shown in Figure 7. It is a level route with a height difference of 21 meter and the ambient temperature was about 20°C.

To determine the driving speed, road types along the route have to be obtained from OSM first, and the result is shown in Figure 8. As can be seen, the main part of the route is highway, but other types of road are also included.

The speed profiles of the prediction and actual measurement along the route are shown in Figure 9. As can be seen, the driving speed on the highway ranges from 80 km/h to 120 km/h, as the driver normally can choose his own driving speed on highway. This will obviously lead to different energy consumption results. To provide more information to the driver, different energy consumption results are calculated for a driving speed from 80 km/h to 120 km/h with an interval of 10 km/h. The energy consumption is calculated based on the model described in reference,\textsuperscript{25} the results are shown in Figure 10. The mean value of actual highway driving speed is 104 km/h. It can be seen that the measured energy consumption is also between the energy prediction results for speed profiles of 100 and 110 km/h. This illustrates the accuracy of the offline algorithm.

According to OSM, most rural and city roads are primary roads, secondary roads, tertiary roads and unclassified roads.\textsuperscript{35} For city and rural driving, the driver has to follow the traffic flow. Therefore, apart from the nominal prediction, the maximum and minimum prediction values are used to define the energy consumption range for city and rural driving.

One rural driving test, performed on 25 November 2014 in the Eindhoven area, is shown here as an...
example. The speed profiles of the prediction and actual measurement are shown in Figure 11. It can be seen that the predicted nominal speed is close to the actual value. The energy consumption of predictions and measurement are shown in Figure 12. The difference between the nominal prediction and measurement is approximately 5%.

Before a trip begins, the offline algorithm can give a first estimation of the expected energy consumption. However, the energy consumption is also influenced by the vehicle usage and driving behavior during driving. Driving behavior is different for various drivers, and it may also vary for one driver from time to time. Vehicle usage can also result in changes of the energy consumption. Some examples of conditions that will result in an increased energy consumption are: switching on interior heating, increasing the number of passengers in the vehicle and the tyre rolling resistance will increase when they are not inflated properly.

The initial values of these parameters used in the offline algorithm may be not accurate for the actual trip. To improve the energy consumption prediction accuracy, an online algorithm is designed to update the offline algorithm prediction result using vehicle measurements while driving.

The structure of the online energy consumption prediction algorithm is shown in Figure 13. Vehicle speed and motor output power are measured to estimate the vehicle mass and rolling resistance. Then the estimated vehicle parameters are used to adjust the maximum and minimum energy consumption prediction. The nominal energy consumption prediction result is adjusted based on the current driving behavior. The energy consumption model is the same as used for the offline algorithm.
A simplified example on how to adjust the offline energy consumption prediction results using measurement data is shown in Figure 14. Only one type of road is considered in this example. The maximum, nominal and minimum speed profiles of the offline prediction are shown in (a), taking into account of the influence of road slope and head wind, see (b) and (c), the energy consumption results are predicted, as shown in (d). After a distance $s_2$ is driven, the online algorithm has gathered enough data and starts to adjust the offline predicted energy consumption results. The estimated values of the vehicle mass $m$ and rolling resistance coefficient $f_r$ from the parameter estimation algorithm are shown as the solid lines in (f) and (g). It can be seen that estimated mass and rolling resistance are lower than the default values used in offline algorithm indicated by the dashed lines. Hence, the estimated vehicle parameters $m$ and $f_r$ are used to update the maximum and minimum energy consumption prediction based on the predicted maximum and minimum speed profiles. The maximum energy consumption prediction $E_{\text{max}}$ and the minimum energy consumption prediction $E_{\text{min}}$ are adjusted by the online algorithm, as the dotted lines in (h). However, because the road slope and head wind are different for future driving compared to the past recording between $s_1$ and $s_2$, as shown in (b) and (c), the future nominal energy prediction value should be corrected by taking the influence of road slope and head wind into consideration. The corrected nominal energy consumption prediction $E_{\text{nom\_correct}}$ from online algorithm is labelled in (h). This is hence the best estimate for the nominal energy consumption prediction.

### Parameter estimation algorithm

The vehicle mass, tyre rolling resistance coefficient and auxiliary system usage are important parameters that influence the vehicle energy consumption. To improve the energy consumption prediction accuracy, these parameters need to be determined while driving.

The auxiliary system usage is determined by the driver, the basic auxiliary power equals 210 W and this value will increase to 1800 W when the heating system is working. The auxiliary system power usage can be measured directly during driving. The vehicle mass is changed by vehicle loading, cargo and number of passengers, so it may be varying for each trip. Although the relationship between the rolling resistance coefficient and ambient temperature is already obtained beforehand, the rolling resistance coefficient is also dependent on the tyre and road condition. It is difficult to measure the vehicle mass and rolling resistance directly during driving. A recursive least-squares (RLS) estimation algorithm is used to estimate these two parameters.

The RLS estimation algorithm relies on the vehicle longitudinal dynamics model. The motor output power $P_m$ during driving is

$$P_m = T_w = \left( F_r + F_{\text{aero}} + F_g + F_m + F_{fr} \right) v$$  \hspace{1cm} (7)

where $F_{fr}$ is the powertrain friction force in wheels, the value is 15 N.

Equation (7) can be rewritten as

$$T_w = \left( F_{\text{aero}} + \left( \frac{4J_w}{p^2} + \frac{J_m}{p^2} \right) a_x + F_{fr} \right) v = \left( f_r mg \cos(\alpha) + m g \sin(\alpha) + m a_x \right) v$$  \hspace{1cm} (8)

Rearranging equation (8) in a linear estimation format given:

$$y = \varphi^T \theta$$  \hspace{1cm} (9)

where

$$y = T_w = \left( F_{\text{aero}} + \left( \frac{4J_w}{p^2} + \frac{J_m}{p^2} \right) a_x + F_{fr} \right) v$$  \hspace{1cm} (10)

$$\varphi = \begin{bmatrix} g \cos(\alpha) v \\ g \sin(\alpha) v + a_x v \end{bmatrix}$$  \hspace{1cm} (11)
Figure 15. Online estimation of rolling resistance coefficient and vehicle mass.

\[ \theta = \begin{bmatrix} f \, m \\ m \end{bmatrix} \]  
\[ (12) \]

The classical RLS method is chosen to minimize the following loss function:

\[ V(\hat{\theta}, t) = \frac{1}{2} \sum_{j=1}^{t} (y(j) - \varphi^T(j)\hat{\theta})^2 \]  
\[ (13) \]

A recursive solution is adopted from the book *Adaptive Control*:30

\[ \hat{\theta}(t) = \hat{\theta}(t-1) + K(t)(y(t) - \varphi^T(t)\hat{\theta}(t-1)) \]  
\[ (14) \]

where

\[ K(t) = P(t-1)\varphi(t)(I + \varphi^T(t)P(t-1)\varphi(t))^{-1} \]  
\[ (15) \]

\[ P(t) = (I - K(t)\varphi^T(t))P(t-1) \]  
\[ (16) \]

In the RLS estimation, the sample time is chosen as one second. \( P(t) \) is normally referred as the covariance matrix, which needs enough data to converge, the initial value of \( P \) is set to be the identity matrix. The default value of the vehicle mass in the estimation algorithm is 1250 kg, including the curb mass of 1060 kg and load of 190 kg. The default value of the rolling resistance coefficient is 0.012. This leads to \( \hat{\theta} = [15 \, 1250]^T \) as the initial estimate.

The estimation of rolling resistance coefficient and mass for a rural road driving test that has been done in the Eindhoven area on 20 November 2014 is shown in Figure 15. It can be seen that the estimation of both rolling resistance and vehicle mass are fairly constant after 0.1 h driving. The vehicle mass has some variation most likely caused by measurement errors, but the variation is smaller than 4% and rolling resistance is almost constant. These variations in the first 0.1 h may be caused by the RLS algorithm needing enough data to converge and possibly the tyres needing to warm up at the beginning of the trip resulting in a lower rolling resistance after some time has passed.

**Driving behavior correction algorithm**

The driving behavior can be defined by acceleration, speed and proportion of the idling time. Although the driving characteristics of a driver can be quantified in terms of historical recordings, it is still influenced by traffic flow and route information for one trip. Therefore, the driving behavior is assumed to be the same for a specific road type during one trip instead of modelling it. Thus the future energy consumption can be adjusted based on the current recordings.

However, the driving behavior may also be changed by the traffic flow for future driving. Although this change cannot be predicted in advance, the algorithm should be able to adjust the prediction result based on recent changes. The driving behavior correction algorithm hence has to fulfill two requirements:

- Provide a stable prediction result if the driving behavior is constant.
- Adjust the prediction result based on the recent changes in driving behavior.

The driving behavior correction algorithm is designed using the route information to fulfill these two requirements. The main idea of the algorithm can be described as the energy consumption per kilometer for future driving \( E_f \) is assumed to be the same as the recent recording on the same type of road, so

\[ E_f = E_p \]  
\[ (17) \]

where \( E_p \) is the energy consumption per kilometer for past driving.

The recording of past driving energy consumption per kilometer can take several forms according to a literature review:31

- **Short recording** (\( E_{p,short} \)): the specific energy consumption is calculated based on a short past distance recording of the current trip. The recording distance can be e.g. 1 km or 2 km.
- **Running recording** (\( E_{p,running} \)): the specific energy consumption is calculated based on the recording from the beginning of the trip to the current location.
- **Long recording** (\( E_{p,long} \)): the specific energy consumption is calculated based on a long historical recording, e.g. 300 km.

However, none of these three forms can fulfill the requirements of the driving behavior correction algorithm. \( E_{p,short} \) is always changing during driving, which can lead to an unstable result. \( E_{p,long} \) is stable, but it
cannot reflect a change of the ambient temperature, driver’s mood and auxiliary usage. \( E_{p,\text{running}} \) can reflect the power usage of the current trip, but it cannot adjust the prediction result timely if the auxiliary system power usage or the road type is changing in the middle of the trip.

To solve these problems, a suitable recording distance should be chosen, which is longer than the recording of \( E_{p,\text{short}} \) and shorter than the recording of \( E_{p,\text{running}} \). A moving average (MA) method \( E_{p,\text{ma}} \) to calculate the specific energy consumption of past driving is chosen, as demonstrated in Figure 16. The recording within a distance \( \Delta l \) is considered to be able to represent the current driving behavior, so the specific energy consumption of past driving can be calculated as

\[
E_{p,ma}(i) = \frac{E(s(i)) - E(s(i) - \Delta l)}{\Delta l} \tag{18}
\]

\( s(i) \) represents the travelled distance at update instance \( i \), given by

\[
s(i) = s(i - 1) + \Delta s \tag{19}
\]

This motivation for an energy consumption prediction update every \( \Delta s \) distance instead of every meter is because the energy recuperation of EVs will cause the energy consumption to have some swings along the driving distance, as shown in Figure 17. The fluctuation of the energy consumption may confuse the driver, so a more stable outcome is preferred, for example, the energy consumption is updated every 500 m for the dashed line. In the algorithm, the update distance \( \Delta l \) is set to 2 km on a highway, 1 km on a primary and trunk road and 0.5 km on other types of road. The recording distance \( \Delta l \) is three times the update distance \( \Delta s \). These two values are chosen based on comparisons between simulations and measurements.

The highway driving test, shown in Figure 9, is used to show the effect of different past recording methods.

The energy consumption prediction error of three recording methods, namely short recording, running recording and MA recording are presented in Figure 18. At the beginning of the trip, the energy consumption predicted value is increasing rapidly, this is because the actual driving speed at the beginning of this trip is higher than the predicted nominal driving speed. It can be seen that the MA recording method is more stable than the short recording and reacts faster than the running recording.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|}
\hline
& MAPE & SDPE \\
\hline
with road slope correction & 3.35 & 4.50 \\
without road slope correction & 6.37 & 4.90 \\
\hline
\end{tabular}
\caption{Online prediction result of the hilly test.}
\end{table}

\textbf{Wind and road slope influence}

There are two other factors that will affect the energy consumption: head wind and road slope. The energy
consumption caused by these two factors for past driving is not the same as the impact on future driving. To improve the prediction accuracy, the energy consumption per kilometer caused by the head wind and road slope in the past has to be excluded and the corresponding value for future driving should be included when calculating the future specific energy consumption $E_f$ using equation (17).

The energy consumption caused by the head wind and road slope can be calculated once the corresponding forces are determined. The contribution of the road slope is independent of the driving speed, and it is only determined by the route, as shown in equation (5). However, the aerodynamic force caused by the head wind $F_w$ is affected by the driving speed, given as

$$F_w = \frac{1}{2} \rho C_d A (v - W)^2 - \frac{1}{2} \rho C_d A v^2$$

(21)

where $W$ is the head wind speed. For past driving, the speed $v$ can be measured, while for future driving, the speed has to be predicted. According to the driving behavior correction algorithm assumption, the average speed in last recording distance $\Delta v$ can represent the average speed of the future driving, thus this value will be used to calculate the future wind force.

Because the same approach is used to deal with the influence of wind and road slope, the road slope influence is chosen as a demonstration to illustrate this improvement. A hilly area driving test described in Table 3 (Test 26) is selected, in this particular case the influence of wind is very small. The road height along the route is shown in Figure 19. It can be seen that the vehicle drives downhill first, and then drives uphill, so the energy consumption of the first half trip is much smaller than during the second half. If the first half

<table>
<thead>
<tr>
<th>Test</th>
<th>Type</th>
<th>Data</th>
<th>Ambient temp. [°C]</th>
<th>Average speed [km/h]</th>
<th>Distance [km]</th>
<th>Energy [kWh]</th>
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</tr>
<tr>
<td>8</td>
<td>Highway</td>
<td>20160421</td>
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<td>64.5</td>
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<tr>
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</tr>
<tr>
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</table>

Note: For highway tests, other types of road are also included, so the average driving speed is lower than 80 km/h.

Figure 19. The height information along a hilly route.
recording is used to predict the future energy consumption, without considering the influence of the road slope, the predicted energy consumption will be smaller than the actual value, as shown by the dashed diamond line in Figure 20. Taking the road slope into consideration can improve the prediction accuracy, as the solid circle line in Figure 20.

The mean absolute percentage error (MAPE) and standard deviation percentage error (SDPE) between the online prediction results and the measured value are listed in Table 2. Comparisons also prove the advantage of considering the influence of road slope.

In Figure 20, the difference between the prediction and measurement at zero driving distance is the offline algorithm prediction error. It be seen that the offline nominal prediction value is lower than the actual energy consumption, this is because the predicted nominal driving speed is lower than the actual driving speed, as shown in Figure 21. The online algorithm starts to update the energy consumption prediction after gathering data on the first two kilometers driven.

Verification by experiments

Driving tests

The energy consumption prediction algorithm is verified by driving tests on the public road using the TU/e Lupo EL. Over 50 channels are measured in the vehicle, including, vehicle speed, motor torque and speed, battery output power, accelerator and brake pedal position.29 The driving tests are done from June 2014 to April 2016 and include highway, city, rural and hilly area driving. A total of 30 tests and more than 700 km have been covered by four different drivers. The highway, city and rural tests are done in the Eindhoven area, whereas the hilly tests are done in the Nijmegen area in the Netherlands. The hilly driving tests have been done in only one day because Eindhoven is a flat area, and the distance between Eindhoven and hilly area is more than 60 km. More hilly driving tests need to be done in future research. During driving, the energy consumption is measured at the high voltage battery terminals. More details on the driving tests are listed in Table 3.

Offline energy consumption prediction verification

It is important to note that the ability to accurately estimate the energy consumption before a trip begins is the most critical task, since the driver uses this estimate to plan his trip. To verify the accuracy of the offline algorithm, the average value of the nominal predicted speed and measured speed are compared in Figure 22. It can be seen that the predicted speed is close to the measured speed. The error of the offline energy consumption prediction results are shown in Figure 23. It can be seen that in most cases the nominal prediction errors are smaller than 10%, and the energy consumption prediction range of all tests captures the measured energy consumption values. Only for one test in the hilly area the difference is bigger than 10%. The reason for this large error is that the actual driving speed was much higher and exceeded the assumed maximum speed, see Figure 21.

Compared to other researches with a prediction error of more than 20%,12,41 the presented offline algorithm considering the influence of route information and weather condition is a significant improvement of the energy consumption prediction.

Online energy consumption prediction verification

There is no acknowledged standard to evaluate the online algorithm at this moment. The MAPE and SDPE between prediction results and the measured energy consumption value are used as a criterion to evaluate the online algorithm. The MAPE is used to evaluate the accuracy and SDPE is used to evaluate the variation of the online prediction result. The reason to choose these two criterions is because the relative error is of importance, not the absolute difference.
The evaluation results of the 30 tests listed in Table 3 are shown in Figure 24. It can be seen that the MAPE and SDPE between the online prediction results and the measured energy consumption value are within 5% for most tests. The evaluation criteria used here are not adopted by all researches in this field. After processing the prediction results of these papers, the MAPE of other papers is around 10%. Therefore, we can draw the conclusion that the online algorithm presented in this research appears to be an improvement.

Conclusions and recommendations

In this paper, an energy consumption prediction algorithm, including an offline and an online part is developed. The energy consumption prediction algorithm is verified by 30 driving tests, including highway, rural, city and hilly driving. The main contributions of the presented work can be summarized as:

1. To provide a base for the driver to make a future driving plan, an offline energy consumption prediction algorithm considering the influence of route information and weather condition is presented. Three energy consumption prediction values are provided: a maximum value, a minimum value and a nominal value. Comparisons between simulations and measurements show that the accuracy of the proposed method has a significant improvement compared to other researches.
2. A moving average method is applied in the online algorithm to adjust the energy consumption prediction result, which can provide a stable prediction if the driving behavior is constant and adjust the prediction timely based on changes of driving behavior.
3. The influence of head wind and road slope on the energy consumption along the driving route is considered in the online algorithm, which improves the online energy consumption prediction accuracy.

In future work, the difference of driving behavior need to be quantified and the vehicle remaining driving range prediction will be based on the methods described in this paper and battery modelling research. Furthermore, a suitable onboard system to inform the driver has to be developed.

Declaration of conflicting interests

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