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Online prediction of battery electric vehicle energy consumption

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Abstract

The energy consumption of battery electric vehicles (BEVs) depends on a number of factors, such as vehicle characteristics, driving behavior, route information, traffic states and weather conditions. The variance of these factors and the correlation among each other make the energy consumption prediction of BEVs difficult. This paper presents an online algorithm to adjust the energy consumption prediction during driving. It includes a vehicle parameter estimation algorithm and a driving behavior correction algorithm. The vehicle parameter estimation algorithm can assess the vehicle mass and rolling resistance during driving. The driving behavior correction algorithm can adjust the energy consumption prediction based on the current driving behavior, and considers the influence of wind and road slope. The online energy consumption prediction algorithm is verified by 21 driving tests, including highway, city, rural and hilly area tests. The comparison shows that the mean absolute percentage error between the actual energy consumption value and online prediction result is within 5% for every test.

Keywords: Battery electric vehicle, energy consumption, prediction, online.

1 Introduction

The limited driving range and long charging time of battery electric vehicles (BEVs) make drivers more concerned on whether they can reach the destination based on the current battery state of charge, this phenomenon is called ”range anxiety”. Range anxiety is considered as one of the major factors that affects the acceptance of BEVs. Besides a bigger battery and more charging facilities, an accurate and reliable energy consumption prediction along a chosen route is also important to reduce the driver’s range anxiety. However, the energy consumption of BEVs is dependent on a number of external factors, such as vehicle characteristics, road topography, driving behavior, traffic state and weather conditions.
The high number of impact factors and the correlation among each other make the energy consumption prediction of BEVs is difficult and complex. Several studies have been performed on predicting the energy consumption of BEVs. They can be mainly divided into two categories: offline energy consumption prediction and online prediction. The offline energy consumption prediction is either by using a physical model or a statistical model obtained from real-world recording data to calculate the energy consumption based on the predicted speed profile before a trip begins [1, 2]. The online prediction is using a regression

model to adjust the energy prediction result based on historical recordings and current driving behavior and route [3, 4].
A regression model can be used to adjust the energy consumption prediction based on current measurements and future route. However, a driving route may contain several road types. When the road type is changing, more than one parameters may change, e.g. the average driving speed and rolling resistance coefficient. The regression model cannot distinguish the influence of different parameters, so the adjustment may not represent the future driving accurately. However, it is easy for a detailed physical model to calculate the energy consumption difference caused by the changing parameters.
This paper presents an online algorithm to adjust the energy consumption prediction using a detailed physical vehicle energy consumption model based on route information. The online energy consumption prediction algorithm takes the influence of the driving behavior, vehicle usage condition and future route information into consideration to improve the prediction accuracy.
The vehicle usage condition may change some vehicle parameters which can influence the energy consumption, e.g. auxiliary system usage, vehicle mass and rolling resistance coefficient. The auxiliary system usage can be measured directed during driving, but the vehicle mass and rolling resistance coefficient cannot be measured directly, and need to be estimated. In this research, the vehicle mass and rolling resistance coefficient is estimated by a recursive least-square (RLS) algorithm using the measured driving speed and motor output power.
The driving behavior can be defined by acceleration, speed and idling time, which is mainly determined by the driver, traffic flow and road type. Although the driving behavior cannot easily be measured and predicted, it can be assumed to be ”constant” on the same road type during one trip [5], thus the future energy consumption can be adjusted based on the current recordings on the same type of road. The route information, including the road type, speed limit signs, traffic lights and elevation data, is obtained from OpenStreetMap (OSM) and Shuttle Radar Topography Mission (SRTM) in this paper.
The structure of the online energy consumption prediction algorithm is shown in Figure 1. During driving, vehicle speed and high voltage battery output power are measured and this measured data is used to estimate two parameters: vehicle mass and rolling resistance. The details on the parameter estimation algorithm and driving behavior correction algorithm are discussed in following sections. The online algorithm is designed to improve an offline energy consumption prediction algorithm, which is presented in reference [2].

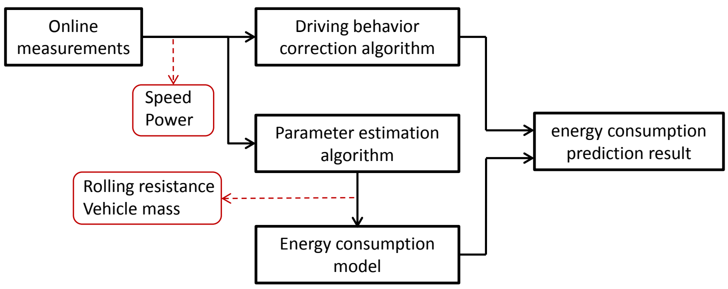

Figure 1: The structure of the online energy consumption prediction algorithm.

An energy consumption model considering the influence of weather conditions and road surface dependent rolling resistance is adopted to determine the energy consumption in this research. The energy consumption model is validated on an electric vehicle, the TU/e Lupo EL, and can calculate the energy consumption within an error of 5% for different circumstances [2]. The TU/e Lupo EL is built from a donor vehicle, VW Lupo 3L, by the Dynamics and Control group of the Eindhoven University of Technology in 2009, and ”EL” is the abbreviation of Electric Lightweight [6, 7, 8].
This paper is organized as follows. In Section 2 the parameter estimation algorithm is introduced. In Section 3 the driving behavior correction algorithm is described. In Section 4 the wind and road slope

correction is discussed. In Section 5, the online energy consumption prediction algorithm is evaluated by driving tests on the public road. In Section 6 the conclusions are given and the future work is discussed.

2 Parameter estimation algorithm

The vehicle mass, rolling resistance coefficient, auxiliary usage and road grade are the most important parameters that will influence the vehicle energy consumption, apart from the driving speed. These parameters may vary from trip to trip and some can even change during one trip. To improve the energy consumption prediction accuracy, these parameters need to be determined during driving. The road slope along a trip can be obtained from SRTM before a trip begins. The auxiliary system usage is determined by the driver and the energy consumption can be measured directly during driving. The mass is dependent on the vehicle load and the rolling resistance coefficient can be easily influenced by the tire condition and weather. These two parameters are difficult to be measured directly. Therefore, a recursive least-squares (RLS) estimation algorithm [9, 10] is used to estimate the vehicle mass and rolling resistance coefficient in this research.

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

$$P_m = T \cdot \omega = (F_r + F_{aero} + F_g + F_m + \frac{T_{fr}}{r}) \cdot v \tag{1}$$

where T is the motor output torque; ω is the motor angular speed; T_{fr} is the wheel bearing and powertrain friction torque; r is the tyre radius and v is the vehicle speed.

The rolling resistance force F_r is

$$F_r = f_r \cdot m \cdot g \cdot cos(\alpha) \tag{2}$$

where f_r is the rolling resistance coefficient; m is the vehicle mass; g is the gravitational constant and α is the road slope. The aerodynamic drag force F_{aero} is given by

$$F_{aero} = \frac{1}{2} \cdot \rho \cdot C_d \cdot A_f \cdot (v - W)^2 \tag{3}$$

where ρ is the air density and W is the wind speed in the driving direction, obtained from a weather website. The force originating from the road slope F_g is

$$F_g = m \cdot g \cdot sin(\alpha) \tag{4}$$

The acceleration force F_m is given by

$$F_m = (m + \frac{4 \cdot J_w}{r^2} + \frac{J_m \cdot i_g^2}{r^2}) \cdot a_x \tag{5}$$

where J_w is the wheel inertia, J_m is the motor inertia, i_g is the gearbox ratio and a_x is the acceleration. At last, Equation (1) can be rewritten as

$$\begin{aligned} T \cdot w - (F_{aero} + (\frac{4 \cdot J_w}{r^2} + \frac{J_m \cdot i_g^2}{r^2}) \cdot a_x + \frac{T_{fr}}{r}) \cdot v = \\ (f_r \cdot m \cdot g \cdot cos(\alpha) + m \cdot g \cdot sin(\alpha) + m \cdot a_x) \cdot v \end{aligned} \tag{6}$$

Rearranging Equation (6) in a linear estimation format as

$$y = \varphi^T \theta \tag{7}$$

where

$$y = T \cdot w - (F_{aero} + (\frac{4 \cdot J_w}{r^2} + \frac{J_m \cdot i_g^2}{r^2}) \cdot a_x + \frac{T_{fr}}{r}) \cdot v \tag{8}$$

$$\varphi = \begin{bmatrix} g \cdot cos(\alpha) \cdot v \\ g \cdot sin(\alpha) \cdot v + a_x \cdot v \end{bmatrix} \tag{9}$$

$$\theta = \begin{bmatrix} f_r \cdot m \\ m \end{bmatrix} \tag{10}$$

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

$$V(\hat{\theta}, t) = \frac{1}{2} \sum_{i=1}^{t} (y(i) - \varphi^T(i)\hat{\theta})^2 \tag{11}$$

The recursive solution is [11]:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + K(t)(y(t) - \varphi^T(t)\hat{\theta}(t-1)) \tag{12}$$
$$K(t) = P(t-1)\varphi(t)(I + \varphi^T(t)P(t-1)\varphi(t))^{-1} \tag{13}$$
$$P(t) = (I - K(t)\varphi^T(t))P(t-1) \tag{14}$$

In the RLS estimation, the sample time is chosen as one second, the initial value of P is set to 1. The starting values of the vehicle mass and rolling resistance coefficient in the energy consumption prediction algorithm are 1250 kg and 0.012 respectively, this leads to $\hat{\theta} = [15\ 1250]^T$.

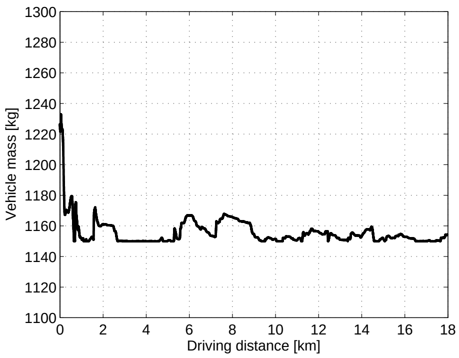

Figure 2: Recursive estimation of the vehicle mass.

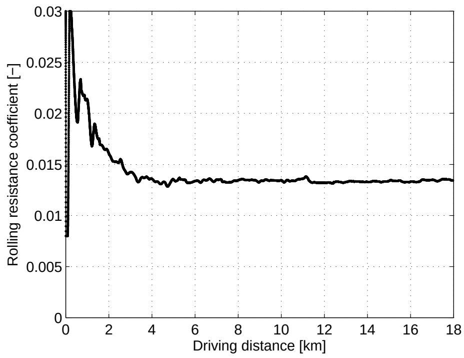

Figure 3: Recursive estimation of the rolling resistance coefficient.

A rural road driving test has been done in Eindhoven area on November 20th 2014. The parameter estimation algorithm is used to estimate the vehicle mass and rolling resistance coefficient. The results are shown in Figure 2 and Figure 3. It can be seen that both estimations of vehicle mass and rolling resistance coefficient are fairly constant after the first three kilometers driving. The vehicle mass has some variation most likely caused by measurement errors, but the variation is smaller than 4%; the rolling resistance coefficient is almost constant. Therefore, these two estimations are considered accurate enough for the energy consumption prediction algorithm. The unstable estimation in the first three kilometers may be caused by tyres needing to warm up at the beginning of the trip and also the algorithm needs enough data to converge to an accurate value.

3 Driving behavior correction algorithm

The driving behavior is considered to be "constant" on the same type of road during one trip, however it may also change 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. Therefore, the driving behavior correction algorithm has to fulfill two requirements:

- Providing 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 based on the road information to fulfill these two requirements. The driving route is divided into several sections based on road type information. There will be one steady driving section for each road type, and also one transitional driving section between two different types of road. A demonstration on how to divide the road sections is shown in Figure 4. As can be seen, sections 2, 4 and 6 are the steady sections, while section 1, 3, 5 and 7 are the transitional sections when going from one road type to another.

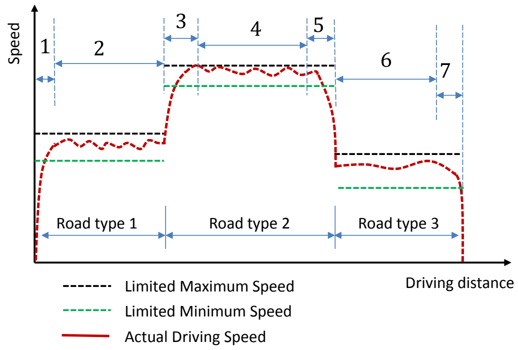

Figure 4: Route sections based on road type.

The driving speed would change very aggressively at the transitional area on a primary road, trunk road and highway road, but it will be stable after the transitional area on these types of road. Therefore, the driving speed in the transitional section cannot represent the future driving speed, a transitional section recording cannot be used to predict the future energy consumption. As a result, the energy consumption recording within steady sections are used to predict the future energy consumption on a primary road, trunk road and highway road. However, the steady road segment is quite short for a city road and the vehicle has to decelerate to a low speed or stop in a intersection and traffic light. Thereby, there is no obvious difference between the transitional section and steady section for city driving. As a result, it is not necessary to distinguish the difference between the transitional section and steady section for a city road.

The length of transitional section is determined by the driver and traffic flow. The transitional length in this research is defined as the distance from the beginning of an acceleration until the vehicle speed stops increasing if the vehicle is accelerating at the beginning of the road type, and vice versa. According to the measurement, the transitional length of the primary road and trunk road ranges from 0.2 km to 0.9 km. To guarantee the accuracy of the algorithm, the transitional length is chosen the maximum value. Therefore, the length of the transitional section is set as 2 km on highway road, 1 km on a primary and trunk road.

The main idea of the driving behavior correction algorithm can be described by

$$\overline{E}_f \approx \overline{E}_p \tag{15}$$

where $\overline{E}_f$ is the energy consumption per kilometer for the future driving, $\overline{E}_p$ is energy consumption per kilometer for the past driving, which is calculated based on the past recording. The past recording can take several forms according to the literature review [3]:

- short recording ($\overline{E}_{p:short}$): 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 ($\overline{E}_{p:running}$): the specific energy consumption is calculated based on the recording from the beginning of the trip to the current location.
- long recording ($\overline{E}_{p:long}$): the specific energy consumption is calculated based on a long historical recording, e.g. 300 km.

However, none of these three items can fulfill the requirements of the driving behavior correction algorithm. $\overline{E}_{p:short}$ is always changing during driving, which can lead to an unstable prediction. $\overline{E}_{p:long}$ cannot reflect a change of the ambient temperature, driver's mood and auxiliary usage, while these factors play an important role in the vehicle energy consumption [12]. $\overline{E}_{p:running}$ can reflect the power usage of the current trip, but it cannot adjust the prediction result timely if the power usage is changing in the middle of a trip.
To solve these problems, the recording distance should be chosen as a suitable value, which is longer than the recording of $\overline{E}_{p:short}$ and shorter than the recording of $\overline{E}_{p:running}$. A moving average method (MA) $\overline{E}_{p:ma}$ to calculate the specific energy consumption of past driving is described, see Equation 16 and 17. A demonstration is shown in Figure 5. In this method, the recording within a distance of Δl is assumed to be able to represent the current driving behavior and used to calculate the past specific energy consumption.

$$\overline{E}_{p:ma}(i) = \frac{E(s(i) + \Delta l) - E(s(i))}{\Delta l} \tag{16}$$

where $s(i)$ represents the travelled distance at instance i.

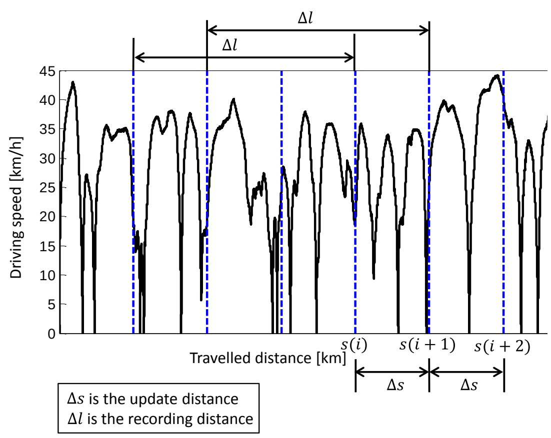

Figure 5: A demonstration of the methodology to chose the recording distance.

The energy consumption prediction result is updated after a distance Δs, given as

$$s(i + 1) = s(i) + \Delta s \tag{17}$$

The reason why the energy consumption is updated every distance Δs instead of every meter is because the energy recuperation of BEVs will cause the energy measurement to have some swings along the driving distance, as shown in Figure 6. It can be seen that the measured energy has some fluctuation during driving, which may confuse the driver when providing the prediction. Therefore, a more linear outcome is preferred for the prediction as the solid line, the energy consumption is determined every 500 m. In this algorithm, the update distance Δs is set as the same value as the length of a transitional section, which is 2 km for a highway road, 1 km for a primary and trunk road and 0.5 km for other types of road. The recording distance Δl is three times the update distance. These two values are chosen based on a comparison between simulations and measurements.

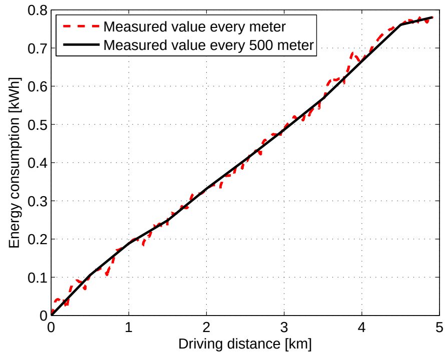

Figure 6: The relationship between the energy consumption and driving distance in a city driving.

A highway driving test is used to show the effect of these different past recording methods. The speed data is shown in Figure 7. The comparison between energy consumption prediction results of three recording methods, namely short recording, running recording and MA recording are presented in Figure 8. At the beginning of the trip, the energy consumption prediction is increasing rapidly, this is because the driving speed at the beginning of this trip is higher than the average highway driving speed of this trip. It can be seen that the MA recording method is more stable than the short distance recording and reacts faster than the running recording.

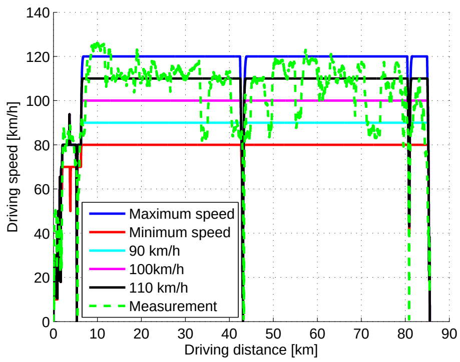

Figure 7: The driving speed for a highway driving route.

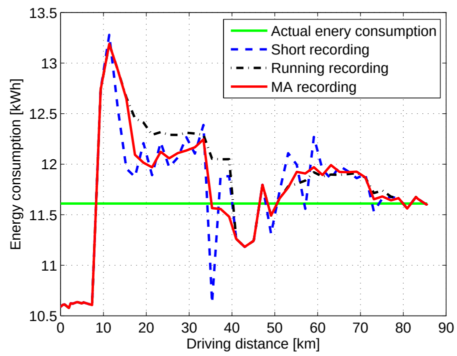

Figure 8: The energy consumption prediction along a highway driving route.

4 Wind and road slope influence

There are two other predictable factors that can affect the energy consumption prediction result: wind and road slope. These two factors are changing along the driving route, therefore, the energy consumption caused by these two factors in past driving cannot represent the contribution in the future. To improve the prediction accuracy, the influence of wind and road slope in the past has to be excluded when calculating the past specific energy consumption $\overline{E}_p$, and the influence of wind and road slope in the future should be included when calculating the future specific energy consumption $\overline{E}_f$.

The algorithm to take the influence of wind and road slope influence into consideration is discussed next. The vehicle is assumed to be driving on one road type. The length of the trip is L, the driving distance from the start point to the current position is l_c, the past recording distance is Δl. Within the past recording distance Δl, the measured energy consumption is E, driving speed is v and head wind speed is W. The energy consumption $\Delta E_{w,p}$ caused by the wind and the energy consumption $\Delta E_{s,p}$ caused by the road slope in the recording distance Δl are calculated first. The energy consumption E_p^* for the same distance without the influence of wind and slope is obtained then. Finally, the specific energy consumption $\overline{E}_p$ without the influence of wind and road slope is calculated.

$$\Delta E_{w,p} = \sum_{i=l_c-\Delta l}^{l_c} \frac{1}{2} \cdot \rho \cdot C_d \cdot A \cdot (v_i - W_i)^2 \cdot ds - \sum_{i=l_c-\Delta l}^{l_c} \frac{1}{2} \cdot \rho \cdot C_d \cdot A \cdot v_i^2 \cdot ds \tag{18}$$

$$\Delta E_{s,p} = \sum_{i=l_c-\Delta l}^{l_c} m \cdot g \cdot sin(\alpha_i) \cdot ds \tag{19}$$

$$E_p^* = E - \Delta E_{w,p} - \Delta E_{s,p} \tag{20}$$

$$\overline{E}_p = E_p^* / \Delta l \tag{21}$$

where i is the travelled distance; ds is the interval distance to calculate the energy, the value is 1 meter. The driving behavior is assumed to be unchange during the trip, therefore, the past specific energy consumption $\overline{E}_p$ and the average driving speed $\overline{v}_p$ are assumed to be the same as the respective values $\overline{E}_f$ and $\overline{v}_f$ of the future driving. The future specific energy consumption $\overline{E}_f$ is then used to predict the energy consumption for the rest of the drive on this road section, and the influence of wind and road slope are included to calculate the future energy consumption E_f.
The future energy consumption results can be calculated as,

$$\overline{E}_f = \overline{E}_p \tag{22}$$

$$\overline{v}_f = \overline{v}_p \tag{23}$$

$$E_f^* = \overline{E}_f \cdot (L - l_c) \tag{24}$$

$$\Delta E_{wind} = \sum_{i=l_c}^{L} \frac{1}{2} \cdot \rho \cdot C_d \cdot A \cdot (\overline{v}_f - W_i)^2 \cdot ds - \sum_{i=l_c}^{L} \frac{1}{2} \cdot \rho \cdot C_d \cdot A \cdot \overline{v}_f^2 \cdot ds \tag{25}$$

$$\Delta E_{slope} = \sum_{i=l_c}^{L} m \cdot g \cdot sin(\alpha_i) \cdot ds \tag{26}$$

$$E_f = E_f^* + \Delta E_{wind} + \Delta E_{slope} \tag{27}$$

where $\overline{v}_f$ is the average speed of future driving; E_f^* is the future energy consumption without the influence of wind and road slope and E_f is the energy consumption for future driving.
Because the same approach is used to deal with the road slope and wind, the road slope is used as a demonstration to illustrate the algorithm. A hilly area driving test is used to show the influence of the road slope on the energy consumption prediction. In this particular case, the influence of wind is very small. If the wind speed is big and the driving direction has a major change, then the influence of wind will also be significant.
The road height information along the hilly route is shown in Figure 9. It can be seen that the vehicle drives downhill first, and then uphill. The energy consumption of the first half of the trip is smaller than the second half. If the recording of the first half trip is used for predicting the future energy consumption without considering the influence of road slope, the prediction value will be smaller than the actual value. This is illustrated by the dashed line in Figure 11. Taking the road slope correction into consideration can improve the prediction accuracy, as indicated by the solid line in Figure 11. The predicted energy

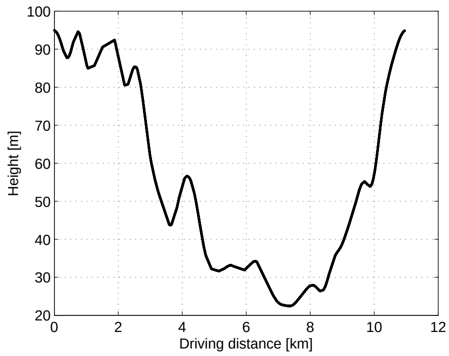

Figure 9: The height information along a hilly route.

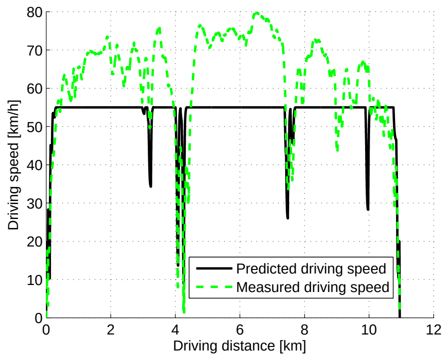

Figure 10: The driving speed along a hilly route.

consumption result is lower than the measured one at the beginning of the trip, this is because the predicted driving speed before the trip begins is lower than the actual driving speed, as shown in Figure 10. The online algorithm starts to update the energy prediction result after gathering the measurement on the first two kilometers.

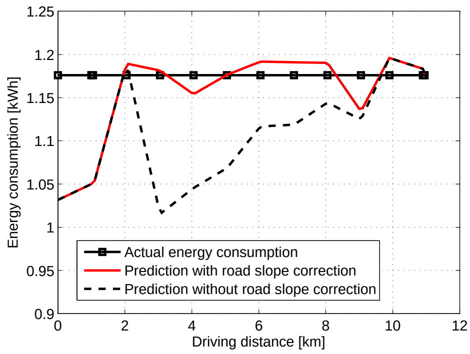

Figure 11: The influence of road slope and wind in a hilly route. (Test 17 in Table 1).

5 Measurement verification

5.1 Driving tests

The online energy prediction algorithm has been verified by driving tests on the public road using the Lupo EL. The driving tests are done from June 2014 to June 2015, and includes highway, city, rural and hilly area tests. A total of 21 tests and more than 600 km have been driven by four drivers. The highway tests, city tests and rural tests are done in the Eindhoven area, while the hilly tests are done in the Nijmegen area in the Netherlands. The energy consumption is measured at the high voltage battery terminals during the driving. Details on the driving tests are shown in Table 1. It should be noticed that for highway test other types of road are also included, so the average driving speed is lower than 80 km/h.

5.2 Online algorithm verification

There is no acknowledged standard to evaluate the online energy consumption prediction algorithm at this moment. Actually, it is impossible to evaluate the online prediction result if the driving behavior shows a major change during a trip, because this change cannot be predicted. But for normal driving, the driving behavior will not change significantly and the accuracy of the online energy consumption

Table 1: Details on driving tests in the Netherlands

Type	Date	Trip number	Ambient temperature $[°C]$	Average speed [km/h]	Distance $[km]$	Energy $[kWh]$
Highway road	20140606	1	22	75.2	60.6	6.66
	20140619	2	17	63.6	43.7	5.85
	20140902	3	20	95.2	101.7	14.89
	20150416	4	12	100.2	71.6	10.94
	20150706	5	23	92.9	114.7	15.00
City road	20141120	6	8	21.0	5.7	0.69
	20141125	7	7	22.4	5.2	0.66
	20141203	8	0	23.9	5.7	0.72
	20150416	9	14	42.5	10.7	2.21
Rural road	20141120	10	8	45.9	18.0	1.92
	20141125	11	7	43.3	18.0	1.87
	20141202	12	2	45.4	18.0	2.13
	20141203	13	0	39.3	18.0	2.06
	20150413	14	12	56.4	26.2	3.45
	20150416	15	21	59.2	20.4	2.42
Hilly road	20150630	16	26.0	52.1	11.0	1.15
		17		54.3	11.0	1.18
		18		49.1	11.0	1.10
		19		48.7	11.0	1.07
		20		56.0	11.0	1.12
		21		51.8	11.0	1.04

prediction can be evaluated. Instead of the mean absolute error (MAE), the mean absolute percentage error (MAPE) and standard deviation percentage error (SDPE) between prediction result and the actual energy consumption value are used as the criterion to evaluate the online energy consumption prediction algorithm in this research. The reason to chose these two criterions is because the relative error is of importance, not the absolute difference. The online prediction of the hilly test described in Section 4 and shown in Figure 11 is evaluated as a demo, and the result is listed in Table 2. Comparisons also prove the advantage of considering the influence of road slope.

Table 2: Online prediction result of the test in Figure 11

	MAPE	SDPE
With road slope correction	3.35	4.50
Without road slope correction	6.37	4.90

The values of MAPE and SDPE of 21 tests are shown in Figure 12. It can be seen that the MAPE and SDPE between the prediction result and the actual energy consumption value are within 5% for most tests. Not all the research on this area use the same standards to evaluate the prediction accuracy [13, 14, 15], but after recalculating the prediction results the MAPE of other papers is around 10%. Therefore, we can draw the conclusion that the online algorithm presented in this research can provide a more accurate prediction result.

6 Conclusions

Battery electric vehicles have a limited driving range compared to ICE vehicles, and it takes a longer time to recharge the battery than to refill the fuel tank. Therefore, an accurate energy consumption prediction along a chosen route is important for an electric vehicle driver. In this paper, an online energy

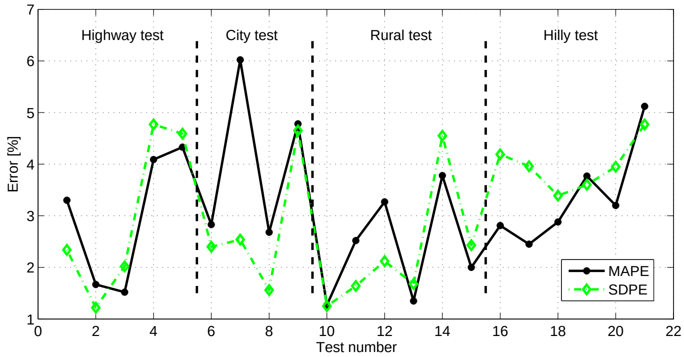

Figure 12: The online algorithm prediction results.

consumption prediction algorithm is described. The online algorithm includes a vehicle parameter estimation algorithm and a driving behavior correction algorithm. The online algorithm can estimate the vehicle mass and rolling resistance coefficient and adjust the energy consumption prediction result based on the current driving behavior.
The online energy consumption prediction algorithm is verified by 21 driving tests on the public road, including highway driving, rural driving, city driving and hilly area driving. The comparison between the actual energy consumption value and online prediction result shows that the MAPE and SDPE of most tests are within 5% during driving. It is therefore believed that the online energy consumption prediction algorithm can be used as a driver assistance system for BEVs. Future work is to design an onboard driver information system based on this research.

Acknowledgments

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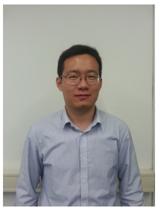

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