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Battery electric vehicle energy consumption modelling for range estimation

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Abstract: Range anxiety is considered as one of the major barriers to the mass adoption of battery electric vehicles (BEVs). One method to solve this problem is to provide accurate range estimation to the driver. This paper describes a vehicle energy consumption model considering the influence of weather conditions and road surface dependent rolling resistance, which includes a road load, a powertrain, a regenerative braking, an auxiliary system and a battery model. The parameters of these models are obtained by different types of experiments. The energy consumption model is verified by 20 driving tests, including highway, rural and city driving. The results show that the proposed model can predict the energy consumption under different circumstances with a maximum error of 5%, which is a clear improvement over the 10% error from a simple energy consumption model. The proposed energy consumption model will be used to build a range estimator in future research.

Keywords: BEV; battery electric vehicle; energy consumption; modelling; weather influence; coast down test; dynamometer test.

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Biographical notes: Jiquan Wang received his MSc from Chongqing University, China, in 2012. He is currently pursuing a PhD within the Dynamics and Control group, Department of Mechanical Engineering, Eindhoven University of Technology. His current research interests include electric vehicle energy modelling, energy consumption prediction, geographical information system application, advanced navigation system and intelligent transportation system.

Igo Besselink received his MSc and PhD from the Delft University of Technology, the Netherlands, in 1990 and 2000, respectively. Between 1991 and 1996, he worked at Fokker Aircraft, located in Schiphol, the Netherlands. In 1996, he moved to TNO Automotive in Delft and worked on tyre testing, modelling and simulation software development. In 2008, he joined the Eindhoven University of
1 Introduction

Range anxiety emerged as a concept in the late 1990s and can be explained as a driver’s concern of not reaching their destination while driving in a battery electric vehicle (BEV). In fact, range anxiety has been identified as one of the main obstacles to the expansion of BEVs (Thomas and Josef, 2013). Many approaches are provided to reduce drivers’ range anxiety, such as improving the battery technology, building more charging facilities and expanding the capacity of a power network. However, these approaches are not easily applied on short notice. Besides, an accurate range indicator system is also necessary to reduce the driver’s range anxiety (Ferreira et al., 2014). Furthermore, based on the range prediction information, the driver can also take some measures to extend the remaining driving range, such as reducing the driving speed or turning off some of the auxiliary systems.

The energy consumption of the vehicle needs to be modelled to predict the remaining driving range of BEVs. The energy consumption is dependent on vehicle characteristics and some characteristics are influenced by the weather conditions (Neaimeh et al., 2013; Nordelöf et al., 2014). There are two methodologies for determining the energy consumption: building statistical models based on real world driving measurements (Shankar and Marco, 2013; De Cauwer et al., 2015; Rodgers et al., 2013) and creating vehicle models based on physics (Dhand and Pullen, 2013; Wu et al., 2015). Using real-world measurements can result in more realistic values for the energy consumption calculation, but it relies on a high number of real-world measurements and cannot be directly coupled with vehicle parameters and environmental conditions. For instance, in De Cauwer et al. (2015) three statistical models are built in terms of multiple linear regression from real-world measurements. The influence of acceleration, elevation and ambient temperature is considered in the regression models, but the nonlinear characteristics of regenerative braking cannot be modelled, which is an important aspect of the BEV driving efficiency.

In contrast, a vehicle energy consumption model based on physics gives a direct link with vehicle dynamics and powertrain characteristics, which makes the identification of the influence of vehicle characteristics and weather on the energy consumption more clear. In this approach, however, detailed values of the driving profile, including speed
and acceleration are needed. Taking advantage of a modern navigation system, the road topography and even real-time traffic information can be obtained (Boriboonsomsin et al., 2012; Jiménez and Cabrera-Montiel, 2014). This can be used as the input for a physical energy consumption model. Some simple physical models with constant vehicle parameters are used to predict the future energy consumption in Dhand and Pullen (2013), Wu et al. (2015) and Abousleiman and Rawashdeh (2014). These models can predict the energy consumption accurately for a specific driving route and a specific weather condition. However, the calculation accuracy will decrease if the driving route and/or weather conditions are changing (Yao et al., 2013; Yuksel and Michalek, 2015; Nordelöf et al., 2014).

The purpose of this paper is to build a physical vehicle energy consumption model considering the influence of weather conditions and road surface dependent rolling resistance. The energy consumption model is built in a reverse way from road load to power socket, which includes a road load model, a powertrain model, a regenerative braking model, an auxiliary system model and a battery model. Several driving tests from May 2013 to December 2014, including highway, rural and city driving, are used to verify this vehicle energy consumption model.

An electric vehicle, the TU/e Lupo EL, is used to support the research presented in this paper. It is built using a VW Lupo 3L as a donor vehicle, where EL is the abbreviation of ‘Electric Lightweight’. The Lupo EL is currently used as a research platform for electric mobility (Besselink et al., 2013; Wang et al., 2015).

This paper is organised as follows. In Section 2, the energy consumption of the vehicle components is analysed and modelled. The experiments to determine the parameters of these models are described. In Section 3, the details of 20 driving tests are given. The accuracy of the vehicle driving model, the vehicle charging model and the full energy consumption model are verified by these driving tests. In Section 4, the conclusions of this paper are made and the future work is introduced.

2 Energy consumption modelling

The energy flow of a BEV can be divided into two processes: charging and driving, see Figure 1. For the charging process, the energy is taken from the power socket. A small part of the energy is used for the vehicle auxiliary system and most of the energy is stored in the vehicle high voltage battery. For the driving process, the electric energy is taken from the high voltage battery, a part is used by the auxiliary system, and most of the energy is transferred by the electric motor into mechanical energy, which is used to overcome the road load.

Figure 1 Energy flow of a battery electric vehicle (see online version for colours)
In this paper, the electric vehicle energy consumption model is built in a reverse way. This means that the vehicle driving speed and acceleration are the model input and the energy taken from the power socket is the model output. For the driving process, the model includes four parts from the vehicle wheel to the battery output: the road load model, the powertrain model, the regenerative braking model and the auxiliary system model. For the charging process, the battery model is built. The parameters of these models are obtained using various measurements.

2.1 Road load

When a vehicle is driving on a road, it will experience resistance forces, the road load, which includes rolling resistance force \( F_r \), aerodynamic drag force \( F_{\text{air}} \) and road slope force \( F_g \). The vehicle’s longitudinal equation of motion according to Newton’s second law is given as

\[
m_{\text{eff}} a_x = F_x - F_r - F_{\text{air}} - F_g,
\]

where \( a_x \) is the vehicle longitudinal acceleration (m/s\(^2\)) and \( F_x \) is the propelling force at wheels (N). The vehicle effective mass \( m_{\text{eff}} \) is the sum of the vehicle mass and the equivalent mass of the motor and wheels inertia. It can be calculated as

\[
m_{\text{eff}} = m + \frac{4 J_w}{R_e^2} + \frac{J_{\text{em}}}{r_d R_e^2},
\]

where \( m \) is the vehicle mass (kg), including occupants and cargo; \( J_w \) is the wheel inertia (kgm\(^2\)); \( J_{\text{em}} \) is the motor inertia (kgm\(^2\)); \( R_e \) is the tyre effective rolling radius (m) and \( r_d \) is the gear reduction ratio (–).

The rolling resistance \( F_r \) equals

\[
F_r = f_r mg \cos(\alpha),
\]

where \( f_r \) is the tyre rolling resistance coefficient (–); \( g \) is the gravitational acceleration (m/s\(^2\)) and \( \alpha \) is the road slope (rad). The aerodynamic drag force \( F_{\text{aero}} \) is given as

\[
F_{\text{aero}} = \frac{1}{2} \rho C_d A_f (v - W)^2,
\]

where \( \rho \) is the air density (kg/m\(^3\)); \( C_d \) is the aerodynamic drag coefficient (–); \( A_f \) is the vehicle frontal area (m\(^2\)); \( v \) is the vehicle speed (m/s) and \( W \) is the wind speed in the vehicle driving direction (m/s). The force originating from the road slope \( F_g \) is

\[
F_g = mg \sin(\alpha).
\]

The propelling force at wheels \( F_x \) thus equals

\[
F_x = f_r mg \cos(\alpha) + \frac{1}{2} \rho C_d A_f (v - W)^2 + mg \sin(\alpha) + m_{\text{eff}} a_x.
\]

To build the road load model, all the parameters in equation (6) should be determined. Since the variability of these parameters is different (see Table 1), parameters are determined
separately. The stable parameters can be obtained by tests, the parameters with an extremely high variability can be measured during driving, the vehicle mass is dependent on the passengers number, and the road slope can be calculated based on the road information. The air density $\rho$ is changing with the weather condition and the rolling resistance coefficient $f_r$ is determined by the weather and road condition. Therefore, air density and rolling resistance coefficient will be changing for different driving conditions. To model the energy consumption, values for these two parameters should be identified under different circumstances.

Table 1 Variability of vehicle longitudinal dynamics equation parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>$g$, $C_d$, $A_f$</th>
<th>$m$</th>
<th>$\rho$</th>
<th>$f_r$</th>
<th>$\alpha$</th>
<th>$a$, $v$</th>
<th>$W$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependency</td>
<td>Passengers</td>
<td>Weather</td>
<td>Road</td>
<td>Road</td>
<td>Traffic</td>
<td>Road</td>
<td>Weather</td>
</tr>
<tr>
<td>Variability</td>
<td>Stable</td>
<td>Low</td>
<td>High</td>
<td>Extremely high</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

2.1.1 Air density

The air density $\rho$ is a function of pressure, relative humidity and ambient temperature. The humidity has a minor influence on the air density at a higher temperature (Picard et al., 2008). According to the equations published by Picard et al. (2008), the value of air density is shown in Figure 2 when the humidity is 80%. As can be seen, the air density will decrease with temperature increase and air pressure decrease.

Figure 2 Air density as a function of ambient temperature and pressure

Source: Picard et al. (2008)

2.1.2 Rolling resistance coefficient

In this research, many coast down tests have been performed to obtain the rolling resistance coefficient $f_r$. During a coast down test, the propulsion is removed when the vehicle reaches
a certain speed, then the resistance force will slow down the vehicle until it comes to a standstill (Karlsson et al., 2011). Besides the road load, the friction in the vehicle powertrain is also a resistance force. The differential equation describing the longitudinal dynamics in a coast down test on a level road equals

\[ m_{\text{eff}} a_x = -f_r m g - \frac{1}{2} \rho C_d A_f (v - W)^2 - F_{\text{fric}}, \]  

(7)

where \( F_{\text{fric}} \) is the powertrain friction force at wheels (N). Its value is obtained from a vehicle wheel free rolling test (Lipsch, 2012). In this test, the vehicle was lifted from the ground and the wheels are accelerated to a speed, just above 100 rad/s. Then the motor is turned off and the wheels are slowed by the friction in the vehicle powertrain. Test results show that the equivalent friction force at wheels is approximately 15 N.

The MATLAB/Simulink Parameter Estimation Tool is used to calculate the rolling resistance coefficient \( f_r \) through minimising the difference between measurement and simulation. The interior point algorithm is applied in the optimisation process. A comparison between simulation and measurement of coast down tests on the highway at different temperatures is shown in Figure 3. The summer test was done on 1st August, 2013, the ambient temperature was about 29\(^\circ\)C and the rolling resistance coefficient \( f_r \) is determined to be 0.0095. The winter test was done on 11th December, 2013, the ambient temperature was about 2\(^\circ\)C and the \( f_r \) is then determined to be 0.0132. Thus the increase of \( f_r \) is about 39% from 29\(^\circ\)C to 2\(^\circ\)C.

Figure 3  Coast down test on highway road for different ambient temperatures (see online version for colours)

The rolling resistance coefficient \( f_r \) is dependent on the road surface, ambient temperature, driving speed and tyre inflation pressure (Michelin, 2003). To obtain the relationship between the rolling resistance coefficient \( f_r \) and these influence factors, coast down tests are done on the various road surface in the neighbourhood of Eindhoven at different times throughout the year. The test date, ambient temperature, road type and rolling resistance coefficient \( f_r \) results are shown in Table 2.

Some empirical equations are adopted in Okubo and Oyama (2014) and Tony (2001) to obtain the relationship between rolling resistance coefficient \( f_r \), ambient temperature
and driving speed. In both of these two references, the heat generated by tyres during driving is also taken into consideration. However, it was not possible to monitor the tyre temperature during driving in our tests. According to these two papers, the increase of tyre temperature is within 15°C during normal driving and the tyre temperature is related to ambient temperature and speed, which is difficult to predict accurately. According to Tony (2001), the variation of rolling resistance coefficient \( f_r \) caused by the speed is smaller compared to the temperature effect. In this paper, it is assumed that tyre temperature will change with ambient temperature. Therefore, only the road surface and ambient temperature are considered to determine the rolling resistance coefficient \( f_r \).

### Table 2  Coast down test results – rolling resistance coefficient

<table>
<thead>
<tr>
<th>Date</th>
<th>Temp (°C)</th>
<th>Highway</th>
<th>City smooth</th>
<th>Rural smooth</th>
<th>Rural coarse</th>
<th>Belgium block</th>
</tr>
</thead>
<tbody>
<tr>
<td>20150715</td>
<td>28</td>
<td>0.0102</td>
<td>0.0105</td>
<td>0.0115</td>
<td>0.0130</td>
<td>0.0135</td>
</tr>
<tr>
<td>20150717</td>
<td>22</td>
<td>0.0108</td>
<td>0.0115</td>
<td>0.0127</td>
<td>0.0145</td>
<td>–</td>
</tr>
<tr>
<td>20151008</td>
<td>12</td>
<td>0.0117</td>
<td>0.0125</td>
<td>0.0132</td>
<td>0.0160</td>
<td>0.0160</td>
</tr>
<tr>
<td>20160229</td>
<td>6</td>
<td>0.0125</td>
<td>0.0148</td>
<td>0.0143</td>
<td>0.0157</td>
<td>0.0183</td>
</tr>
<tr>
<td>20160216</td>
<td>2</td>
<td>0.0130</td>
<td>0.0152</td>
<td>0.0147</td>
<td>0.0165</td>
<td>0.0187</td>
</tr>
</tbody>
</table>

The ambient temperature in the Netherlands is within the range of –10°C to 30°C normally. An algebraic equation is used to describe the empirical relationship between the rolling resistance coefficient \( f_r \) and the ambient temperature \( T_{\text{amb}} \), which is expressed as

\[
    f_r = 8.53 \times 10^{-7} T_{\text{amb}}^2 - 1.50 \times 10^{-4} T_{\text{amb}} + 0.0135,
\]

where \( f_r \) is dimensionless and the unit of \( T_{\text{amb}} \) is °C.

The relationship described by equation (8) and results from experiments are shown in Figure 4. Michelin also published research in this field (Michelin, 2003) and the result is also shown in Figure 4. It can be seen that the trend of rolling resistance coefficient \( f_r \) with the ambient temperature is similar, but the trend is slightly more steep in our measurements compared to Michelin. The influence of the road surface on the \( f_r \) is more important compared to the ambient temperature. The scaling of \( f_r \) on various road surfaces is estimated based on the measurement data in Table 2. If the value of the rolling resistance coefficient \( f_r \) on the highway is considered to 100%, then the scaling factor is 105% on a city smooth road, 115% on a rural smooth road, 135% on a rural coarse road and 140% on a Belgium block road.

### 2.2 Powertrain model

The powertrain of the research vehicle consists of an MES-DEA TIM 600 inverter, an MES-DEA A200-200W water cooled AC induction motor, a Carraro reduction gear differential, drive shafts and wheels. The conversion from electrical energy to mechanical energy is not 100% efficient, so the energy loss within the powertrain has to be considered. The motor and inverter loss are considered together, as it is difficult to determine them individually. The energy loss can be divided into four parts: copper loss, iron loss, friction and windage loss and stray loss. Each type of energy loss is determined by different factors, which makes it difficult to be precisely calculated by physical or mechanical laws. To
determine the power loss, a dynamometer test is done in a lab (Kokke et al., 2014). The motor loss, inverter loss and powertrain friction loss are considered together as the powertrain loss and an empirical equation is used to describe it.

**Figure 4** Effect of ambient temperature and road surface on rolling resistance coefficient (see online version for colours)

![Figure 4](image)

### 2.2.1 Dynamometer experiment

During the dynamometer test, the vehicle’s front wheels are put on the dynamometer and the vehicle is fixed to the ground in the longitudinal direction. The control system of the dynamometer maintains a constant drum speed. A sensor is presented to measure the torque applied to the shaft of the drum. When the drum is running at a constant speed, the output of the vehicle motor is changed by adapting the PWM inverter control signal. When the PWM signal is bigger than 50, the vehicle is in traction mode, and the vehicle is in regenerative braking mode when it is smaller than 50. If the PWM signal equals 50, the vehicle is neither propelling nor braking.

A schematic overview of the experiment is shown in Figure 5. Three power values are measured in this test: $P_{\text{bat}}$, $P_{\text{aux}}$ and $P_{\text{drum}}$. $P_{\text{bat}}$ stands for the power measured at the terminals of the high voltage battery pack (kW); $P_{\text{aux}}$ is the power used by the 12 Voltage auxiliaries of the vehicle (kW), the value at the high voltage side of the DC-DC converter is measured and $P_{\text{drum}}$ is the drum mechanical power (kW).

The electric power $P_{\text{elec}}$ to the inverter is $P_{\text{bat}}$ minus $P_{\text{aux}}$, given as

$$P_{\text{elec}} = P_{\text{bat}} - P_{\text{aux}}.$$  

(9)

The mechanical power available at the wheels $P_{\text{wheel}}$ can be calculated as

$$P_{\text{wheel}} = P_{\text{drum}} - P_{\text{drum}, f} - P_{\text{slip}}.$$  

(10)

where $P_{\text{drum}, f}$ is the drum friction loss and $P_{\text{slip}}$ is the tyre slip loss.

The drum friction power loss $P_{\text{drum}, f}$ is measured in a reference test. In the reference test, the drum is running at some specific constant speeds without the vehicle being present.
The drum power measured in the reference test is to overcome the friction in the drum bearing, the result is shown in Figure 6.

During the dynamometer test, the slip between the tyre and drum is significant when the motor output torque is large and the speed is low. The proportion of the wheel slip power loss can even reach 20% of the wheel mechanical power (Kokke et al., 2014). The wheel slip power loss can be calculated as

\[ P_{\text{slip}} = F_{\text{tyre}} v_{\text{slip}}, \]

where \( F_{\text{tyre}} \) is the tyre tangential force during the experiment (N) and \( v_{\text{slip}} \) is the wheel slip speed (m/s), which is the difference between the measured wheel speed and drum speed.

**Figure 5** Schematic figure of the dynamometer test

**Figure 6** Drum friction power with speed

The longitudinal tyre force can be calculated as

\[ F_{\text{tyre}} = T_{b, \text{eff}} / r_b \]

where \( r_b \) is the drum radius, which equals to 1 metre; \( T_{b, \text{eff}} \) is the drum effective torque (Nm), which is the difference between the drum measured torque and drum friction torque. The drum friction torque can be calculated using the data presented in Figure 6.
As an example, the motor electric power $P_{\text{elec}}$ and wheel mechanical power $P_{\text{wheel}}$ for different inverter control signals when the wheel speed is 62 km/h are shown in Figure 7. The powertrain power loss $P_{\text{ptloss}}$ is the difference between the electric power $P_{\text{elec}}$ and wheel mechanical power $P_{\text{wheel}}$, which can be calculated as

$$P_{\text{ptloss}} = P_{\text{elec}} - P_{\text{wheel}}.$$  

The measured powertrain power loss $P_{\text{ptloss}}$ for different wheel speeds is depicted in Figure 8 as a function of the wheel mechanical power $P_{\text{wheel}}$. When the wheel mechanical power is negative, the vehicle is in regenerative braking mode and the vehicle is in traction mode when the wheel mechanical power is positive. It can be seen that the power loss in the regenerative braking mode and traction mode are not exactly the same, with increased losses for the regenerative braking case in comparison to traction.

Figure 7 The motor power input and output when the vehicle wheel speed is 62 km/h (see online version for colours)

2.2.2 Powertrain loss empirical equations

To avoid using look-up tables, algebraic equations are developed to describe the powertrain power loss. Since the power loss for the traction and regenerative braking mode are different, separate empirical equations are used. When the electric motor is idling, there is still some power loss, which is caused by friction and magnetic flux loss. The idling loss is only related to the motor angular speed. The relationship between the motor idling loss and wheel speed in the dynamometer test is depicted in Figure 9. The motor idling test is the same as a coast down test. The power consumption of the vehicle during a coast down test is also shown in Figure 9.
Figure 8  The relationship between the powertrain loss and the wheel mechanical power at different speeds (see online version for colours)

It can be seen that although the motor idling loss of the dynamometer test is not exactly the same as the coast down test measured value, the trends of the power loss with speed are similar. The vehicle coast down tests have already been conducted many times, and the measurement results are consistently the same, while the motor idling test on the dynamometer has only been performed once. Therefore, the measured value of a coast down test is considered to represent the motor idling loss $P_{idle}$. As can be seen the motor idling power loss is more than 800 W when the speed is above 30 km/h, which is rather high. However, it reduces to 170 W when the vehicle is at standstill. The reason for the high value of the motor high-speed idling loss is not understood at this moment, but the measured value will be used in the empirical equations to calculate the powertrain loss. The empirical relationship between the idling power loss $P_{idle}$ (W) and speed $v$ (m/s) is given by

$$P_{idle} = 0.06v^3 - 4.85v^2 + 116.93v + 170.$$ (14)
The MATLAB/Simulink parameter estimation tool is used to get an empirical equation for the powertrain power loss. The interior point method is applied in the optimisation process. For the traction mode, the empirical equation is

$$P_{\text{pt loss}} = (1.02 \times 10^{-8}v^3 - 2.41 \times 10^{-7}v^2 + 1.65 \times 10^{-6}v)T_w^3 + 4.20 \times 10^{-3}T_w^2 + P_{\text{idle}}.$$  (15)

For the regenerative braking mode, the empirical equation is

$$P_{\text{pt loss}} = 2.98 \times 10^{-3}T_w^2 + 0.36|T_w|v + P_{\text{idle}},$$  (16)

where $T_w$ is the wheel mechanical torque (Nm).

The difference of power loss between the empirical equations and the measurement is depicted in Figure 10. It can be seen that the error is smaller than 0.5 kW in most cases. The empirical equations are considered to be sufficiently accurate and will therefore be used to determine the powertrain loss for various driving conditions.

**Figure 10** The powertrain loss difference between simulations and measurements (see online version for colours)

The powertrain efficiency is calculated using equations (15) and (16). In the traction mode, the efficiency $\eta_{\text{pt}}$ can be calculated as

$$\eta_{\text{pt}} = \frac{P_{\text{wheel}}}{P_{\text{wheel}} + P_{\text{pt loss}}}. \hspace{1cm} (17)$$

While in the regenerative braking mode, the efficiency $\eta_{\text{pt}}$ can be described as

$$\eta_{\text{pt}} = \frac{|P_{\text{wheel}}| - P_{\text{pt loss}}}{|P_{\text{wheel}}|}. \hspace{1cm} (18)$$

To take the motor specifications into consideration, the powertrain efficiency map is described in terms of motor torque $T_m$ and angular speed $\omega_m$, which are given as

$$T_m = T_w/i_g, \hspace{0.5cm} \omega_m = vi/g/R_e, \hspace{1cm} (19)$$

where $i_g$ is the gear reduction ratio. The powertrain efficiency map is shown in Figure 11.
2.3 Regenerative braking

A parallel regenerative braking control strategy is implemented in the Lupo EL. The existing VW Lupo 3L hydraulic braking system, including the ABS functionality, is not modified. The regenerative braking system is added to the hydraulic braking system. To ensure reliable braking, the regenerative braking is completely disabled in case of the ABS system becoming active. To model the energy recuperation, the proportion of the regenerative braking force in the entire braking force should be identified for different conditions.

2.3.1 Hydraulic braking

The characteristics of the hydraulic braking system are measured on a brake test bench (Broeksteeg, 2011). The relationship between the hydraulic brake force and brake pressure is depicted in Figure 12(a) and the relationship between the brake pedal travel and brake pressure is depicted in Figure 12(b).

The brake pressure is not the same in the press and release phase for the same brake pedal travel because of hysteresis effects. To simplify the model, the mean value of the brake pressure between the press and release phase is used. The brake pressure is almost zero when the brake pedal position is below 20%. This is most likely because of the required free movement of the brake pedal before the friction material contacts the brake discs. This free stroke is utilised to maximise regenerative braking when using the brake pedal, while the friction brake is hardly being used.

2.3.2 Parallel regenerative braking

A parallel regenerative braking control strategy has been designed based on the brake pedal travel. The relationship between the regenerative braking force at wheels and brake pedal travel is shown in Figure 13(a). At the beginning of the brake application, the force is increased quickly to maximise regenerative braking, but when the brake travel is more than 60%, the regenerative braking force is decreased to zero to ensure vehicle stability in emergency cases. The regenerative braking force is not only controlled by the brake travel
but also is restricted by motor and inverter settings. The maximum regenerative braking power at different vehicle speeds, obtained from driving tests, is depicted in Figure 13(b).

**Figure 12** Hydraulic brake characteristics: (a) the relationship between the hydraulic brake force and brake pressure and (b) the relationship between the brake pedal travel and brake pressure

**Figure 13** Regenerative braking characteristics: (a) the designed regenerative braking force at wheels with brake pedal travel and (b) the maximum regenerative braking power at various speeds measured during driving tests

With these limitations, the relationship between the regenerative braking force and brake pedal travel at some specific speeds is obtained and shown in Figure 14. It can be seen that the relationship between the maximum regenerative braking force and speed is nonlinear, which cannot provide a consistent brake pedal feel. For a specific speed, the sum of regenerative braking force and hydraulic braking force provides the total brake force, this is shown as a function of brake pedal travel in Figure 15. With this information, the regenerative braking force can be calculated based on the vehicle driving speed and deceleration.
It can be seen that this parallel regenerative braking control strategy has two disadvantages. The first issue is that the maximum regenerative brake force is dependent on the speed and the relationship is nonlinear, which may not provide a consistent brake pedal feel. The second issue is that the hydraulic braking system is nearly always used during braking, which results in part of the kinetic energy being transferred into heat. To improve the energy efficiency and brake feel, a one-pedal-driving algorithm is applied in the vehicle now, which is introduced in Van Boekel et al. (2015).

2.4 Auxiliary power

The high voltage power is converted with a DC/DC converter to 12 V power to supply the auxiliary systems. The actual power consumption of auxiliary systems depends on the components which are active. The low voltage power consumption of the auxiliary system components is depicted in Figure 16 when the heating system is not turned on. Measurements
show that the auxiliary system demands about 83 W from the low voltage system when the vehicle is charging and 150 W when the vehicle is driving. The average efficiency of the DC/DC converter is approximately 72% according to measurements, but on some occasions lower values, for example, 60% were also seen. For the modelling process, the auxiliary power $P_{aux}$ demand from the high voltage system is selected as 210 W during the driving process and 115 W during the charging process.

Figure 16  Auxiliary system power consumption (see online version for colours)

2.5 Battery model

The battery pack of the Lupo EL consists of 91 LiFePO$_4$ cells in series, with a nominal energy capacity of 27 kWh and a nominal voltage of 300 V. Based on the recommendation of the battery manufacturer, only 80% of the battery capacity is used for driving to guarantee a battery cycle life of at least 2000 cycles.

Since limited measurement data is available for the battery, a simple equivalent circuit model is used to model the battery, as shown in Figure 17. The relationship between the current and voltage can be written as

$$V_{oc} = V_{out} + IR,$$

where $V_{oc}$ is the battery open circuit voltage (V), $V_{out}$ is the battery output voltage (V), $I$ is the battery output current (A) and $R$ is the battery internal resistance (Ω).

The $V_{oc}$ is in fact not constant; the value is affected by the battery state of charge and temperature (Kroeze and Krein, 2008). The Lupo EL is always parked in the lab and the temperature is almost constant, which equals 20°C. When the vehicle is driving outside, the battery will generate some heat and the vehicle coolant system will work. According to measurements for various driving tests, see Figure 18, the temperature increase of the battery pack for all tests is below 10°C. Therefore, the influence of temperature on the battery performance is neglected in this research.

The $V_{oc}$ of a battery cell is obtained from a battery cell discharge test. The whole battery pack $V_{oc}$ is then obtained by multiplying the number of cells. The relationship between the battery pack $V_{oc}$ and the battery discharging capacity is depicted in Figure 19.
Figure 17  A simple battery equivalent circuit model

Figure 18  The increase of battery temperature in driving tests

Figure 19  The relationship between the $V_{oc}$ and battery discharging capacity

The relationship between the battery output voltage and current during a driving test is depicted in Figure 20. The measured current has both positive and negative value; the positive value is the discharging current, measured when accelerating or driving at constant speed,
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while the negative value is the charging current, measured during regenerative braking. The graph shows that the internal resistance is almost the same for the regenerative braking (charging) and driving (discharging). The measurements of several driving tests are used to determine the battery internal resistance based on equation (20). Because of the hysteresis phenomenon in batteries, the battery internal resistance is calculated during steady state conditions, e.g., constant speed driving. An empirical equation is used to represent the relationship between the internal resistance \( R \) (\( \Omega \)) and battery current \( I \) (A), including charging and discharging, given as

\[
R = -3.84 \times 10^{-7}|I|^3 + 2.04 \times 10^{-5}|I|^2 - 3.7 \times 10^{-3}|I| + 0.41.
\]  

The comparison results of the empirical equation and measurements are shown in Figure 21. This characteristic is used for both positive and negative currents.

**Figure 20** The relationship between the battery output voltage and current during a driving test

![Figure 20](image_url)

**Figure 21** The relationship between the battery internal resistance and discharging current

![Figure 21](image_url)

3 Verification by measurements

3.1 Driving tests

Driving tests on public roads have been done to verify the energy consumption model. A total of 20 driving tests from May 2013 to December 2014, including highway, city and rural
driving have been done. Two energy consumption values are measured in these tests: the battery output DC energy $E_{out}$ measured during driving and the power socket AC energy $E_{ac}$ measured during charging. The details of these tests and measured energy results are listed in Table 3. For some driving tests, the vehicle was not charged immediately after driving, therefore, the AC energy consumption values of some driving tests are missing. For simulations, the battery output DC energy and power socket AC energy are calculated using the vehicle energy consumption model and then compared with the measured values.

Table 3  The driving details data and energy measurement results

<table>
<thead>
<tr>
<th>Test</th>
<th>Date</th>
<th>Ambient temp (°C)</th>
<th>Average speed (km/h)</th>
<th>Distance (km)</th>
<th>DC energy (kWh)</th>
<th>AC energy (kWh)</th>
</tr>
</thead>
</table>
| Highway
| 1   | 2013/05/06 | 21                | 65.8                | 228.9        | 22.60          | 28.02           |
| 2   | 2013/05/16 | 11                | 66.8                | 59.2         | 8.12           | 9.94            |
| 3   | 2013/05/21 | 12                | 83.8                | 114.1        | 14.84          | 18.05           |
| 4   | 2013/05/22 | 11                | 90.0                | 114.1        | 17.51          | 21.45           |
| 5   | 2013/05/27 | 17                | 90.0                | 114.1        | 16.61          | 20.65           |
| 6   | 2013/05/28 | 20                | 81.5                | 114.1        | 13.77          | 16.81           |
| 7   | 2013/05/30 | 14                | 71.6                | 114.2        | 11.92          | 14.42           |
| 8   | 2013/06/17 | 23                | 98.0                | 113.9        | 18.40          | 23.00           |
| City
| 9   | 2013/06/05 | 21                | 22.2                | 47.7         | 5.20           | –               |
| 10  | 2013/06/06 | 23                | 22.3                | 49.6         | 5.44           | –               |
| 11  | 2013/11/27 | 6                 | 23.8                | 50.1         | 6.76           | 8.60            |
| 12  | 2014/11/25 | 7                 | 16.3                | 7.9          | 0.99           | –               |
| 13  | 2014/12/02 | 2                 | 19.3                | 7.9          | 1.14           | –               |
| 14  | 2014/12/03 | 0                 | 17.4                | 7.9          | 1.14           | –               |
| Rural
| 15  | 2013/06/07 | 24                | 35.0                | 33.6         | 3.66           | –               |
| 16  | 2013/07/12 | 17                | 35.1                | 114.2        | 14.55          | 17.60           |
| 17  | 2014/11/20 | 7                 | 37.7                | 18.0         | 2.07           | –               |
| 18  | 2014/11/25 | 7                 | 37.7                | 18.0         | 1.96           | –               |
| 19  | 2014/12/02 | 2                 | 41.8                | 18.0         | 2.21           | –               |
| 20  | 2014/12/03 | 0                 | 36.0                | 18.0         | 1.96           | –               |

3.2 Vehicle driving model verification

The driving model can calculate the battery output DC energy $E_{out}$ based on the driving speed and weather conditions, which is the combination of road load, powertrain, regenerative braking and auxiliary system. During driving, the battery output power $P_{out}$ (W) can be calculated as

$$P_{out} = F_{r}v + P_{ptloss} + P_{aux}.$$  \hspace{1cm} (22)

Then the calculated battery output energy $E_{out}$ (Wh) is

$$E_{out} = \int_{0}^{t_{dri}} P_{out} dt$$ \hspace{1cm} (23)

where $t_{dri}$ is the driving time.
To check the effect of the weather conditions, a simplified model without considering the influence of weather conditions is used to calculate the energy consumption results as well. In the simplified model, air density and rolling resistance coefficient are assumed to be constant. The mean values of driving tests measurement are used: the air density is 1.21 kg/m$^3$; the rolling resistance coefficient is 0.012. The energy consumption calculation errors of these two models are depicted in Figure 22. It can be seen that the maximum error of the driving model considering the influence of weather conditions is approximately 5%, however, the error will increase to about 10% when the influence of the weather conditions is not considered. This justifies the use of a more detailed model.

Figure 22 The calculation error of the vehicle driving model (see online version for colours)

The relationship between the calculation error and the ambient temperature for the simplified driving model is shown in Figure 23. As can be seen, the calculation error is influenced by the ambient temperature. The minimum error is when the ambient temperature is about 15$^\circ$C, the increase of energy consumption is approximately 10% when the ambient temperature increases by 15$^\circ$C.

3.3 Vehicle charging model verification

The vehicle charging model can calculate the power socket AC energy consumption based on the measured battery output DC energy during driving. The energy flow from the power socket to the battery output is shown in Figure 24. The charging process is demonstrated by the red line in Figure 24, the energy is taken from the power socket, a small part is used by the vehicle auxiliary system and consumed by the battery internal resistance, the main energy is charged into the battery. The discharging process is demonstrated by the black line in Figure 24, most of the energy is taken from the stored energy except a small part consumed by the battery itself due to internal resistance.

Based on the measured battery output energy, the AC energy extracted from the power socket $E_{ac}$ (Wh) can be calculated as

$$E_{ac} = (E_{out} + \int_0^{t_{aux}} t_{aux}^2Rdt + t_c^2Rt_c + P_{aux+t_c})/\eta_{charger}$$  \hspace{1cm} (24)
where $I_{\text{dri}}$ is the battery current during driving (A); $I_c$ is the charging current (A); $t_c$ is the charging time (h); $P_{\text{aux}}$ is the auxiliary system power usage during charging (W) and $\eta_{\text{charger}}$ is the charger efficiency (90.4%).

**Figure 23** The relationship between the calculation error and ambient temperature for the simplified driving model

![Graph showing the relationship between calculation error and ambient temperature](image)

**Figure 24** The energy flow from the power socket to the battery output (see online version for colours)

![Energy flow diagram](image)

To verify the effect of variable internal resistance, a simplified battery model with constant internal resistance is used to calculate the AC energy consumption. For the simplified battery model, the internal resistance is set as 0.3 $\Omega$, which is the average value of measurements. The errors of these two vehicle charging models are shown in Figure 25. It can be seen that both of the maximum errors of these two battery models are smaller than 3%, however, the maximum error of the battery model using variable internal resistance is approximate 1% lower than the simplified battery model. Therefore, the battery model with variable battery internal resistance is a more accurate representation.
3.4 Full energy consumption model verification

The adopted vehicle driving model and charging model are combined together as the full vehicle energy consumption model. This model can calculate the energy taken from the power socket based on the driving speed, road information and weather conditions. A simplified full energy consumption model with constant air density, rolling resistance and battery internal resistance is also used to calculate the energy consumption result. The comparison result between the simulations and measurements is shown in Figure 26. As can be seen, the maximum error between the simulations and measurements for the adopted full energy consumption model is approximate 5%, compared with a maximum error about 10% of the simple energy consumption model. The mean absolute error of the adopted full energy consumption model is about 3.2%, which is smaller than the simple model with a value of 4.2%. The standard deviation of the error of the adopted model is 1.6%, which is better
Battery electric vehicle energy consumption modelling for range estimation

than the value of 3.1% of the simple model. Therefore, this adopted energy consumption model is considered sufficiently accurate to represent the vehicle energy consumption for a vehicle range estimator.

4 Conclusions

Building an accurate range estimator for a BEV is an effective way to reduce the driver’s range anxiety. Apart from the driving speed and road topography, the vehicle energy consumption is also influenced by the vehicle characteristics, and some of them are influenced by the weather conditions. In this paper, an electric vehicle energy consumption model is built, taking into account the influence of the weather conditions and road surface. Parameters of the model are obtained through different kinds of experiments.

Driving tests, including highway, rural and city driving are done to verify the vehicle energy consumption model. The results demonstrate that the adopted full energy consumption model with considering the influence of weather conditions, road surface and variable battery internal resistance can calculate the vehicle energy consumption based on the driving speed with a maximum error of 5% under different circumstances, which is better than the maximum error of 10% for a simplified model. The adopted full energy consumption model is considered to be accurate enough to represent the vehicle energy consumption. In future work, the battery self-discharge will be considered in the battery model and the energy consumption model will be used to build an online range estimator.

References


