Energy Consumption Prediction for Electric City Buses

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Abstract
Similar to electric vehicles for the consumer market, the driving range of battery electric city buses is still a limiting factor for market adoption. Furthermore, this driving range can vary depending on environmental conditions, the number of passengers, and driver behavior and is therefore often uncertain. This results in conservative charging strategies and an increased total cost of ownership of the vehicle. This paper presents a physics based energy consumption prediction model, aimed at electric city buses, with the goal of reducing the uncertainty regarding the energy consumption of the vehicle. The model is derived from first principles and complemented by dedicated measurements of an electric city bus, including dynamometer tests and coastdown measurements. Validation using real-world data shows that the model has the ability to accurately predict the consumed energy for the majority of the analyzed trip, although deviations, probably caused by road slope effects, do occur.

Keywords:
electric vehicle, city bus, energy consumption

1 Introduction
Over the last decades, battery research advancements have led to increased energy density and reduced costs of battery packs [1]. These developments, together with the favorable legislation for electric mobility with respect to fossil fuel based transportation [2], sparked a renewed interest in Battery Electric Vehicles (BEV’s). The rate of adoption of BEV’s varies across different markets. While diesel is generally still regarded as the most cost efficient solution for long distance road-freight transport, the passenger car sector is slowly evolving towards electric propulsion as the new standard. In the public transport sector, BEV implementation is also gaining traction [3]. In all sectors, the rate of adoption seems to be limited by the battery powered alternatives having inferior driving range with respect to their fossil fuel counterparts. This results in ‘range anxiety’ experienced by BEV drivers and fleet operators, which is amplified by unreliable range predictions [4]. In the public transport sector, this uncertainty in range prediction gives rise to conservative charging strategies, resulting in unnecessarily long charging times, sub-optimal timetables, and the use of more (redundant) vehicles compared to a fossil fuel powered fleet. While increasing the available battery capacity will resolve the range anxiety, this solution is not always
trivial due to cost, weight, and space constraints. Therefore, until future generation batteries are developed, a more suitable method to decrease range anxiety can be found in developing more accurate energy consumption models to supply more reliable information to both drivers and public transport fleet operators. While the power drawn from the main battery of a BEV also includes the auxiliary components, such as the HVAC system, the pneumatic system and low voltage electronics, this paper focuses on predicting the power consumed by the powertrain, as this power varies significantly as function of a number of vehicle and environmental parameters and it is generally the most significant energy consumer of the vehicle.

1.1 EVERLASTING
The Horizon 2020 project EVERLASTING (Electric Vehicle Enhanced Range, Lifetime And Safety Through INGenious battery management) aims to develop innovative technologies to improve the reliability, lifetime and safety of lithium-ion batteries by developing more accurate, and standardized, battery monitoring and management system [5]. These novel battery technologies will be demonstrated in two vehicles, one of which is a battery electric city bus. This vehicle is also the subject of the study presented here and is henceforth denoted as the ‘EVERLASTING demonstrator’. Among other technologies, the EVERLASTING demonstrator will be able to accurately predict the future power request and energy consumption of the driveline of the vehicle, as function of the route that will be driven.

1.2 Problem Statement
While energy consumption models are widely researched for passenger cars [6–8], the available literature on electric city buses is more limited. Furthermore, much of the research that is available relies on historic data from a single vehicle or a fleet of monitored vehicles. This data-dependency makes it difficult to apply the result to a specific vehicle, such as the EVERLASTING demonstrator. Therefore, this paper presents a physics-based energy consumption model for the EVERLASTING demonstrator. In addition to the advantage of straightforward adaptation to different types of vehicles, the physics-based approach also yields more insight in the energy consumption processes and allows for better extrapolation of the results to more diverse operating conditions.

1.3 Approach
First, a literature overview on energy consumption models is presented in Section 2. In Section 3 the physics of the longitudinal dynamics of the vehicle are explained to derive an energy consumption model. Where a purely first principles approach is difficult or impractical, dedicated measurements are supplied to provide realistic parameters for the model in Section 4. The resulting energy consumption model is compared against real-world measurements in Section 5, after which conclusions and future model extensions are summarized in Section 6.

2 Literature Overview
Vehicle energy consumption models are an extensively researched topic. The models serve different purposes, ranging from development of eco-driving algorithms [9], to parameter sensitivity studies [7], driver behaviour research [10], range prediction [6], and energy management and charging strategy studies [11]. Regardless of the purpose of the models, the aim is to predict the energy consumption of the vehicle, often as function of a set of vehicle- and environmental parameters.
2.1 Literature on Energy Consumption Models
There are generally two classes of energy consumption models: physics based models and data-driven models. Physics-based models [6,11,12] apply the available knowledge of the energy consuming physics. This often includes modeling of the longitudinal dynamics of the vehicle and the powertrain, thereby aiming to accurately mimic the physical components of the vehicle. The models are often a ‘backwards simulation’ of the actual power flow, starting from the dynamics of the vehicle to finally calculate the electrical power requirements at the battery terminals. While the derivation of the model equations is generally straightforward and well understood, the challenge lies in accurately predicting or measuring the relevant input parameters for the models.

Data-driven methodologies [13] are based on statistical models describing correlations between certain input parameters and the vehicle’s energy consumption. In general, the models are derived by identifying statistical relations in sets of real-world data. If this data is available, these models allow to capture complex relations between the parameters and the vehicle energy consumption. However, the quality of the model depends heavily on the available data and accuracy not ensured in case the model is used to extrapolate outside the range of the available data. Furthermore, as the model parameters often no longer represent a physical quantity, insight in the underlying physics is lost. There are studies that combine a physics-based and data-driven approach, such as [8], where the applied methodology is mainly data-driven, but with a model structure that is strongly based on the underlying physics.

2.2 Energy Consumption of Electric City Buses
In the energy consumption modeling field, some research is specifically aimed at energy consumption models for electric city buses. In [14], an electrical-mechanical road load model of an electric bus is developed and verified using real-world data. Different models for the electric drive are investigated, ranging from an efficiency map, wherein all the losses are lumped into one parameter, to a more complicated electric model of the inverter and motor. Results show a 5% error in energy consumption between measurement and simulation, in case an efficiency map is used.

3 A Physics Based Energy Consumption Model
In this section, the applied methodology is explained. The longitudinal equations of motion of the vehicle are used to derive expressions for the energy consumption of the powertrain. Furthermore, the relevant input parameters for the model are discussed.

3.1 Longitudinal Vehicle Dynamics
Figure 1 shows a side-view of a vehicle with all longitudinal forces acting on it. The longitudinal dynamics of the vehicle can be described by

\[ m_{\text{eff}} a_x = F_x - F_{r,f} - F_{r,r} - F_{\text{aero}} - \sin(\alpha) F_g, \]

where \( m_{\text{eff}} \) is the effective mass of the vehicle and \( a_x \) is the longitudinal acceleration. The effective mass includes the rotational inertia of the wheels and powertrain components that also experience rotational acceleration when \( a_x \) is non-zero. For busses, the effective mass is typically 102% of the total vehicle mass. The right-hand side of (1) describes the various forces acting longitudinally on the vehicle and include the driving force \( F_x \), the combined rolling resistance force \( F_r = F_{r,f} + F_{r,r} \), the aerodynamic drag force \( F_{\text{aero}} \), and the longitudinal component of gravity \( F_g \).
The driving force of the vehicle can be expressed as

\[ F_x = \eta \frac{P_{DC}}{V}, \]  

where \( \eta \) is the overall powertrain efficiency between battery and wheels, \( P_{DC} \) is the electrical DC power drawn from the battery by the powertrain and \( V \) is the vehicle velocity. The rolling resistance is modelled as

\[ F_r = f_r \frac{F_g \cos(\alpha)}{m g}, \]  

where \( f_r \) is the rolling resistance coefficient, \( \alpha \) is the local road gradient, and \( F_g \) is the gravitational force according to

\[ F_g = m g, \]  

where \( g \) is the gravitational acceleration and \( m \) is the vehicle mass. Lastly, the aerodynamic drag force is modelled as

\[ F_{aero} = \frac{1}{2} \rho C_d A_f V^2, \]  

where \( \rho \) is the air density, \( C_d \) is the aerodynamic drag coefficient, and \( A_f \) is the frontal area of the vehicle.

Substituting the above relations into (1) and rearranging, results in

\[ P_{DC} = \frac{V}{\eta} \left( m_{eff} a_x + f_r m g \cos(\alpha) + \frac{1}{2} \rho C_d A_f V^2 \sin(\alpha) m g \right). \]

This is a closed form expression for the power drawn from the battery by the powertrain, as function of the velocity \( V \) and longitudinal acceleration \( a_x \), a set of vehicle parameters \( (\eta, m, C_d, \text{ and } A_f) \), and a set of environmental parameters \( (f_r, \alpha, \rho, \text{ and } g) \). Assuming the motion of the vehicle, e.g. the velocity profile as function of time, is known, the challenge lies in accurately determining each of the model parameters.

### 3.2 Input Parameters

In reality, the model parameters mentioned above are not constant, as is shown in Table 1. Note that the variability of some model parameters changes with respect to research performed for passenger cars, such as [6], when electric city buses are considered. For this study, it is assumed that the constant model parameters \( g \) and \( A_f \) are easily measurable or known. However, other parameters might be more challenging to determine and are discussed below individually.
Table 1: Model parameters and their variability for city buses, adapted from [6, Table 1].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Dependency</th>
<th>Variability</th>
</tr>
</thead>
<tbody>
<tr>
<td>$g, A_f$</td>
<td>-</td>
<td>constant</td>
</tr>
<tr>
<td>$C_d$</td>
<td>relative wind direction</td>
<td>low</td>
</tr>
<tr>
<td>$\rho$</td>
<td>weather</td>
<td>low</td>
</tr>
<tr>
<td>$m$</td>
<td>passenger load</td>
<td>high</td>
</tr>
<tr>
<td>$\eta$</td>
<td>velocity, torque, temperature</td>
<td>high</td>
</tr>
<tr>
<td>$f_r$</td>
<td>road, weather</td>
<td>high</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>road</td>
<td>high</td>
</tr>
</tbody>
</table>

3.2.1 Aerodynamic Drag Coefficient
Even though, as indicated in Table 1, the aerodynamic drag coefficient is a function of the relative wind direction, this correlation is difficult to determine for a specific vehicle. Also, when driving at high velocities, the influence of the relative wind direction is reduced. Therefore, in this study, $C_d$ is assumed to be constant. While it is possible to determine $C_d$ using Computational Fluid Dynamics (CFD), this method requires exact knowledge of the geometry of the vehicle and extensive computational effort and knowledge. Therefore, a more pragmatic approach is used and coastdown measurements are used to determine $C_d$ experimentally. These tests are discussed in Section 4.2.

3.2.2 Air Density
As already shown by [6], the variability of the air density can be taken into account in a vehicle energy consumption model. For this, the equations from [15] are used to express the air density as function of ambient temperature, ambient pressure and relative humidity. These environmental weather variables are obtained from the Royal Netherlands Meteorological Institute (KNMI) [16].

3.2.3 Vehicle Mass
In contrast to a passenger car, the total vehicle mass of a city bus can vary significantly during a route, due to variations in the number of passengers. However, exact real-time data on the passenger loading is difficult to obtain. Therefore, in this initial study, the vehicle mass $m$ is assumed to be constant.

3.2.4 Powertrain Losses
In (6), the powertrain efficiency $\eta$ summarizes the power losses that occur between battery and wheels. This single quantity actually represents multiple individual physical losses. Figure 2 shows the topology of the powertrain of the considered vehicle. The power flow starts as DC current at the battery terminals and flows through the inverter to the electric motor. The resulting mechanical power is transferred through a driveshaft to the rear axle. This rear axle contains a differential gearing unit and additional reduction gears. Finally, the mechanical energy is transferred to the road through the tires. Note that the efficiency of the battery is not taken into account in this study.
Inside and in between each of these powertrain components, energy losses can occur. These are summarized below:

1. **Electrical losses.** These include
   
   (a) **Ohmic losses** in both DC cables between battery and inverter and the 3-phase AC cables between the inverter and the motor.
   
   (b) **Losses in the inverter.** The inverter suffers from ohmic and switching losses of the switch-mode converter, which can be approximately 3 to 4% of the total power [17, p. 266].
   
   (c) **Losses in the motor.** These also include ohmic losses. For induction motors these comprise 55 to 60% of the total motor losses at full load [17, p. 262]. Furthermore, there are magnetic core losses, these typically comprise 20 to 25% of the total motor losses. Further losses are due to mechanical friction in the motor (2.a) and other losses that are difficult to specify further.

2. **Mechanical friction.** Generally, all components that are lubricated experience friction and will heat up during driving, thus energy is lost here. These losses include
   
   (a) **Bearings** in the motor, differential housing and uprights.
   
   (b) **Constant velocity joints** of the driveshaft.
   
   (c) **Gears:** in the rear axle.
   
   (d) There can also be **unintended (dry) mechanical friction**, for instance in the brakes that are not fully released.

3. **Tire slip.** All tires experience slip. This can be longitudinal slip of driven/braked wheels but also lateral slip.

Because it is challenging to predict all these losses individually based on first principles, the lumped powerlosses of the powertrain is determined through measurements, as is described in Section 4.1.

### 3.2.5 Rolling Resistance Coefficient

The vehicle experiences rolling resistance on all tires contacting the road. The rolling resistance force is caused by the continuous deformation at the tire-road contact patch of the rolling pneumatic tire. Due to the visco-elastic nature of the rubber in the tire, energy is lost in this process, resulting in a resistance force. This effect is captured by the rolling resistance coefficient $f_r$.

The physics that underly the rolling resistance are complex. Even though physics-based models exist that simulate the rubber deformation that results in rolling resistance, these models often include large finite element simulations of the tire and require extensive knowledge of the tire construction and material properties. Even if this information is available, the numerical models have difficulty with finding
accurate rolling resistance coefficient values, due to the many factors that can influence rolling resistance [18, p. 60]. These factors include the tire itself (dimension, structure, and material), tire temperature, tire pressure, and road condition, which further includes road surface roughness and wetness.

Due to the complexity of the rolling resistance phenomenon, it seems preferable to determine \( f_r \) in an alternative manner, that is representative of the real-world driving conditions of the vehicle. Therefore, the rolling resistance coefficient used in this study is determined through vehicle coastdown measurements, as is explained in Section 4.2.

3.2.6 Road Gradient
In (6) it can be seen that the road gradient has influence on the energy consumption. However, in the current paper, this effect is assumed negligible, because only relatively flat routes in the Netherlands are considered.

4 Dedicated Measurements
As discussed in Section 3, not all input parameters for the physics based energy consumption model can be determined in a straightforward manner. Especially the powertrain efficiency, the aerodynamic drag coefficient, and the tire rolling resistance are parameters that represent the effect of complex physical processes. Therefore, this study deviates from its first-principles approach with respect to these three parameters and determines these through dedicated vehicle tests.

4.1 Dynamometer Measurements
The combined powertrain efficiency \( \eta \), as discussed in Section 3.2.4, is measured for the EVERLAST-ING demonstrator. The methodology from [19] is used in these tests. The vehicle is fixed on the TU/e Heavy Duty Chassis Dynamometer, with the driven wheels of the vehicle in contact with the drum of the dynamometer. This drum can be powered or braked using a 260 kW electric motor. A schematic of this setup is shown in Figure 3.

![Figure 3: Schematic of the dynamometer measurement. Adapted from [6].](image)

During the measurement, various variables are recorded. A shunt sensor measures the DC electrical power transferred between the battery and the inverter \( P_{DC} \). This gives an accurate value for the total power that is consumed or regenerated by the powertrain. Furthermore, the dynamometer setup contains sensors to measure the rotational velocity of the drum and the torque applied to the drum. This allows for the calculation of the total mechanical power applied at the driven wheels of the vehicle \( P_{\text{wheel}} \).
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The purpose of the test is to determine the power loss in the powertrain $P_{ptloss}$ as function of the motor torque and angular velocity. Assuming the powertrain of the vehicle is in steady-state, e.g. no forces/torques are required for the acceleration of masses or inertias, the power loss is defined as

$$P_{ptloss} = P_{DC} - P_{wheel}. \quad (7)$$

The powertrain efficiency $\eta$ is then defined as the ratio between the power flowing out of the driveline and the power entering the driveline. As this powerflow is reversed when switching between driving and regenerative braking, two definitions for $\eta$ are used:

$$\eta_{drv} = \frac{P_{wheel}}{P_{wheel} + P_{ptloss}} \quad \eta_{brk} = \frac{|P_{wheel} - P_{ptloss}|}{|P_{wheel}|}, \quad (8)$$

where $\eta_{drv}$ and $\eta_{brk}$ apply for driving and regenerative braking situations, respectively.

4.1.1 Measurement Results

The results of the dynamometer efficiency measurements are shown in Figure 4(a) as function of motor angular velocity and motor torque. The figure shows the normalized powertrain efficiency $\eta_{norm}$, which is defined as

$$\eta_{norm} = \frac{\eta}{\max(\eta)}. \quad (9)$$

The results show that the powertrain efficiency varies significantly as function of motor torque and that the regenerative efficiency, e.g. the shown efficiency for negative torques, is generally lower than the driving efficiency. Due to torque limitations of the experimental setup, high torque regions of the efficiency map could not be measured. Therefore, the found relation for $P_{ptloss}$ is extrapolated into these regions of the map, as shown in Figure 4(b). Furthermore, the figure shows that the operating points from the recorded validation data, discussed in Section 5, are mostly within the measured part of the efficiency map.

![Figure 4: Normalized efficiency map, as function of motor speed and normalized motor torque. The black lines indicate the motor torque limit.](image)

Coastdown tests are performed to determine estimates for both the aerodynamic drag coefficient $C_d$ and the tire rolling resistance coefficient $f_r$. During such a test, the vehicle is accelerated up to a certain speed, after which the propulsion force is removed, e.g. the vehicle is put into ‘neutral gear’. During the
coastdown that follows, the vehicle slows down under the influence of the road load forces summarized in Section 3. From the velocity profiles recorded during several of such measurements, estimates for $C_d$ and $f_r$ can be derived.

Several of these coastdown measurements are performed using the EVERLASTING demonstrator. By performing the test at various geographical locations, thereby changing the road surface, the rolling resistance coefficient is determined for several road surfaces, ranging from Belgian blocks to good quality asphalt. A comparison between the measurement results and the rolling resistance coefficient provided by the tire manufacturer is shown in Figure 5. It shows that the rolling resistance can vary according to the quality of the road. The figure also shows that the manufacturer supplied value is roughly in accordance with the average value of the measurements. Both for $f_r$ and $C_d$, the average value as obtained from the measurements is used for the energy consumption model.

![Rolling resistance ranges per road type](image)

**Figure 5**: Ranges for the dimensionless rolling resistance coefficient found on various road surfaces. Values are scaled such that the manufacturer provided value is $f_r = 1$.

5 Model Validation

The energy consumption model is validated using measurement data from a real-world trip of a vehicle comparable to the EVERLASTING demonstrator. During the trip, the longitudinal vehicle velocity $V$ is measured, along with the power consumption of the driveline. The measured velocity profile as function of time $V(t)$ and its time derivative $a_x(t)$ are used as input for the energy consumption model.
Figure 6: Discharged and regenerated energy from the vehicle battery, from measurement and estimated by the energy consumption model.

Figure 6 shows the energy discharged and regenerated by the powertrain, as measured on the vehicle and as estimated by the model. As expected, the total accumulated energies increase during the trip, where regenerated energy is defined as negative. The results show that the model closely approximates the measured discharged energy. However, there are larger deviations visible in the recharged energy profile. The majority of this error originates from the period between 370 s and 400 s.

Zooming in on this time period reveals that, while in reality a considerable amount of energy is regenerated, the model predicts barely any charging or discharging. A more detailed analysis of the driven route reveals that the driven road section during this time had a downward slope, which allowed the monitored vehicle to regenerate energy. Because road gradient effects are not included in the current version of the model, the regenerated energy is under-estimated.

6 Conclusions and Outlook

An energy consumption model is derived for the EVERLASTING demonstrator, using a first principles approach. For model parameters that are less trivial to determine, dedicated experiments are conducted.

The powertrain efficiency is measured using a chassis dynamometer and is mapped as function of motor speed and motor torque. Differences are visible between the efficiency for regenerating conditions compared to driving conditions. Secondly, the rolling resistance coefficient is measured on different road-surfaces by use of coastdown tests. The measured rolling resistance coefficient is largely in agreement with the manufacturer provided value, and shows small deviations depending on road surface quality. The coastdown test also yields an estimate for the aerodynamic drag coefficient.

With the measured parameters as input, the energy consumption model is validated using a recorded bus trip. The model output is compared to the measured energy consumption of the powertrain of the vehicle. The results show that for the majority of the trip, the model is able to approximate the measured energy consumption relatively closely. However, the deviations during one particular time period in the simulation indicate that road slope effects have a significant influence on the energy prediction.
6.1 Outlook

The validation in this paper is based on real-world data from a single recorded trip. The resulting analysis shows that particular route characteristics can have a large influence on the model results. Therefore, to better assess the overall accuracy of the model, data from multiple trips, recorded under more varying conditions, should be used.

The energy consumption prediction model can be improved by supplying better estimates for several of the model parameters, as listed in Table 1. As indicated by the model validation, including road height information to supply a road gradient to the model will improve the results. As the height profile from a GPS-signal is rather unreliable, it would be advisable to extract this information from a height-map, was done by [6] for a passenger car. Further parameter estimates that could be improved are the rolling resistance coefficient, which could be adapted depending on road type. Also the aerodynamic model can be improved by taking into account wind velocity and relative wind direction.

Additionally, if the model were to be implemented online, up-to-date information of the vehicle velocity and energy consumption could be used to further improve and adapt the model predictions. Furthermore, online prediction could also be used to estimate parameters from the additional sensor data available on the vehicle.

References


