Powertrain Modeling and Range Estimation of The Electric Bus

Donkyu Baek

School of Electronics Engineering
Chungbuk National University
Cheongju, Republic of Korea
Email: donkyu@cbnu.ac.kr

***Abstract*—The driving range of Battery Electric Vehicles (BEVs) has been fairly extended during recent years, as a consequence of improvements in energy density of lithium-based batteries. As the scope of application of electric vehicles has expanded, electric motors have been used in trucks and buses, as well as simple passenger vehicles. There are several issues in electric buses for the decision of daily route and finding the optimal battery size. In this work, we propose and incorporate an electric bus powertrain model into a range estimator that takes into account slope, speed limits as well as traffic information. We introduce two case studies as applications of the proposed range estimator: (i) the fast route decision and (ii) the iteration-based bus battery sizing.**

***Keywords*–Electric vehicle; powetrain model; range estimator.**

I. Introduction

Although most of the recent Battery Electric Vehicle (BEV) models have significantly extended the driving range (even less costly EVs can reach the 200-250 miles autonomy), range anxiety is still perceived as a major issue. This is due to both the limited battery performance, which largely depends on working and operating conditions, and the still lacking installations of charging stations, especially in Europe [1].

All BEVs include some form of a real-time driving range estimator based on battery State-of-Charge (SoC). Many researchers have addressed the issue of improving the estimator by accounting for all the possible factors contributing to energy consumption: among others, road topology and grade, speed, acceleration/deceleration, weather conditions, vehicle current location, use of on-board electric devices (e.g., A/C), and driving styles (e.g., normal vs. aggressive) [2][3].

As electric motors are used in various types of gasoline vehicles, electric buses have also been introduced on the market [4]. The bus is a good candidate for converting the gasoline powertrain system into an electric power system because of the motor's characteristics, such as being emission free, having low noise, having small vibration, being easy to maintain, etc. However, there are several issues with using electric buses in the public transportation system. We should know which route is more efficiency for the electric bus considering the road slope and the traffic. Also, for a given bus route, optimal battery sizing is another issue. Performing driving tests with different battery sizes is the most obvious way to find the optimal battery size, however, this is very time consuming.

In this work, we propose an electric bus powertrain modeling and simulation framework. We first implement several parameters and component models for a complex vehicle simulation system. Then, we implement an equation-form powertrain model to reduce runtime for energy simulation by extracting coefficients from complex simulation results. The powertrain model is incorporated in a range estimator that updates EV power consumption along with a given driving cycle characteristics including road slope, speed limit and traffic conditions.

The proposed fast electric bus powertrain model and range estimator are useful for runtime decision making and off-line battery sizing. We introduce two case studies as applications of the proposed range estimator: (i) the fast route decision and (ii) the iteration-based bus battery sizing.

The paper is organized as follows: Section II reports the related work; Section III describes the system models (i.e., powertrain, battery and route models) and the powertrain modeling process. Section IV reports simulation results and case studies. Finally, Section V draws some conclusions.

II. Background and Related Work

As a consequence of the worldwide increase in the number of BEVs, the automotive industry is facing some new challenges related to battery pack volume, weight, lifetime and cost. Furthermore, nowadays charging stations are not widespread in all geographical areas, and charging time is still too long with respect to the traditional refueling [5].

While driving range estimation is not a significant issue for Internal Combustion Engine Vehicles (ICEVs), it is more challenging for BEVs because some parameters largely affect the lithium-based battery pack energy at each charge/discharge cycle: current rate, temperature, and even driving style [6][7]. Despite the progress made in producing battery cells with similar energy yield at different discharge currents, depleting a battery at different rates generally leads to different total capacity (Ah) [8]. On top of that, the maximum battery energy decreases over time, even in case of non-connection to a load, as a consequence of deteriorating chemical processes [9].

There are many published papers addressing the issue of energy analysis and optimization in EVs. Most of these works leverage upon linear battery models [10]–[12] and, therefore, they do not include some important non-linear characteristics, such as the real dependency of battery voltage, current and efficiency to SoC. This non-linearity is sometimes just approximated [13] or described by a rather simplified mathematical model as in [14], where the authors proposed a steady-state (i.e., resistive) equivalent circuit. Three energy prediction methods are presented in [15]; however, the related framework should be simplified in order to have a more practical application. Recently, some papers suggest non-linear battery simulation working with EV driving simulation [16][17].

III. System Model and Estimation

A. Powertrain Model

The power consumption of an EV depends on body shape including facial area, curb weight, road slope and types of tires as well as on the speed and acceleration of the EV. Figure 1 shows the dynamic power by a motor rotating with torque T and angular velocity ω. Four resistances are acting on a vehicle, where F_R, F_G, F_I, and F_A are the rolling, gradient, inertia and aerodynamic resistances, respectively.

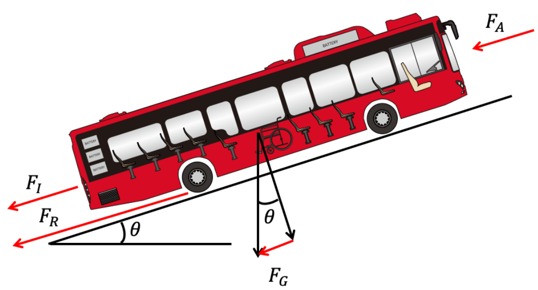

Figure 1. Forces on an EV.

The power consumption at the EV powertrain is the following [16][17]:

$$P_{dyna} = T\omega = F\frac{ds}{dt} = Fv = (F_R + F_G + F_I + F_A)v$$
$$F_R \propto C_{rr}W,\ F_G \propto W sin\theta,\ F_I \propto ma,\ F_A \propto \frac{1}{2}\rho C_d A v^2$$
$$P_{dyna} \approx (\alpha + \beta sin\theta + \gamma a + \delta v^2)mv \tag{1}$$

where C_{rr}, W, θ, m, v, a, C_d, A are the rolling coefficient, weight, road slope, vehicle mass, vehicle speed, acceleration, drag coefficient, and vehicle facial area, respectively. This relation is simplified as a function of four coefficients α, β, γ and δ.

The powertrain efficiency of the electric motor and drivetrain is less than 100%. The efficiency depends on the operating RPM (revolutions per minute) and torque when the EV drives. On top of that, the drivetrain mechanical movement causes a power loss while delivering power to the wheels. The following EV specific power model considers power losses by the motor and drivetrain [17]:

$$P_{EV} = P_{dyna} + C_0 + C_1 v + C_2 v^2 + C_3 T^2 \tag{2}$$

where C_0, C_1, C_2, and C_3 are the coefficients for constant loss, iron and friction losses, drivetrain loss, and copper loss, respectively.

Unlike ICEVs, the electric motor works like a power generator when EV reduces its speed. This is done by a regenerative braking system, which converts the kinetic energy on the wheel into electric energy and sends it to the battery. The power generation by regenerative braking is modeled by a function of the negative motor torque and vehicle speed, as follows:

$$P_{regen} = \epsilon T v + \zeta \tag{3}$$

where ϵ and ζ are regenerative braking coefficients.

B. Powertrain Modeling Process

There are several powertrain simulators in academia and industry. ADvanced VehIcle SimulatOR (ADVISOR) is one of well-organized vehicle simulators that takes into account various factors of vehicles including engines, electric traction motors, types of drivetrains, shape of chassis, etc. [18]. It is possible to implement a certain type of vehicle in ADVISOR by setting powertain parameters and simulating various vehicle driving environments by changing its powertrain or driving profile. Power consumption, battery state of charge and emission over time are simulated for a given driving cycle and vehicle setup.

ADVISOR, however, is not suitable to simulate power consumption in a live manner because of its relatively long runtime. ADVISOR considers overall vehicle dynamics and energy flow from torque on the wheels to the engine or battery pack. Overall vehicle simulation results show energy flow in detail, and this is important for energy analysis. However, it is not efficient to estimate the current load from the battery point of view and make a decision to find the optimal route or vehicle velocity.

Based on the arguments above, instead of using ADVISOR itself, we adopt the vehicle powertrain models from (1) to (3) and use ADVISOR for the extraction of model coefficients. Figure 2 shows the overall process for the electric bus characterization. The process consists of three phases: i) parameter extraction phase, ii) modeling phase and iii) simulation phase.

1) Parameter extraction phase: First, we choose a vehicle for the ADVISOR simulation. ADVISOR requires several parameters and models for the simulation (e.g. motor model, vehicle chassis model and battery model). Vehicle manufacturers officially unveil their vehicle specifications on their website, such as the maximum motor power and torque and the time to reach 100 km/h. This information is used to implement detailed parameters and models for ADVISOR. In this parameter extraction phase, we implement an electric motor model and a drivetrain efficiency model, and a battery model for the ADVISOR simulation. We implement a motor torque map from the maximum motor torque/RPM, the time to reach 100 km/h and vehicle curb weight. We then implement a motor efficiency map using the torque map, battery size and driving range. The drivetrain efficiency model is obtained from the driving range and resistances acting on a vehicle where we calculate resistances using the vehicle body shape and the type of tires. The battery model is easily obtained from battery architecture and the battery cell specification. These models are imported into the ADVISOR system and used to simulate the complex energy flow.

2) Modeling phase: ADVISOR simulates energy flow with an electric vehicle model obtained from Section III-B1 and a driving cycle. We perform simulations to obtain plentiful driving data with various vehicle speeds and road slopes. The simulation results include power consumption by vehicle speed and road slope over time. The driving cycles include driving on flat road with various vehicle speeds and accelerations on various road slopes. Test driving on various road slopes is also performed. We use a multi-variable linear regression method to extract coefficients of the powertrain models from (1) to (3) [17].

3) Simulation phase: The equation form powertrain model from (1) to (3) is used to extract the power consumption

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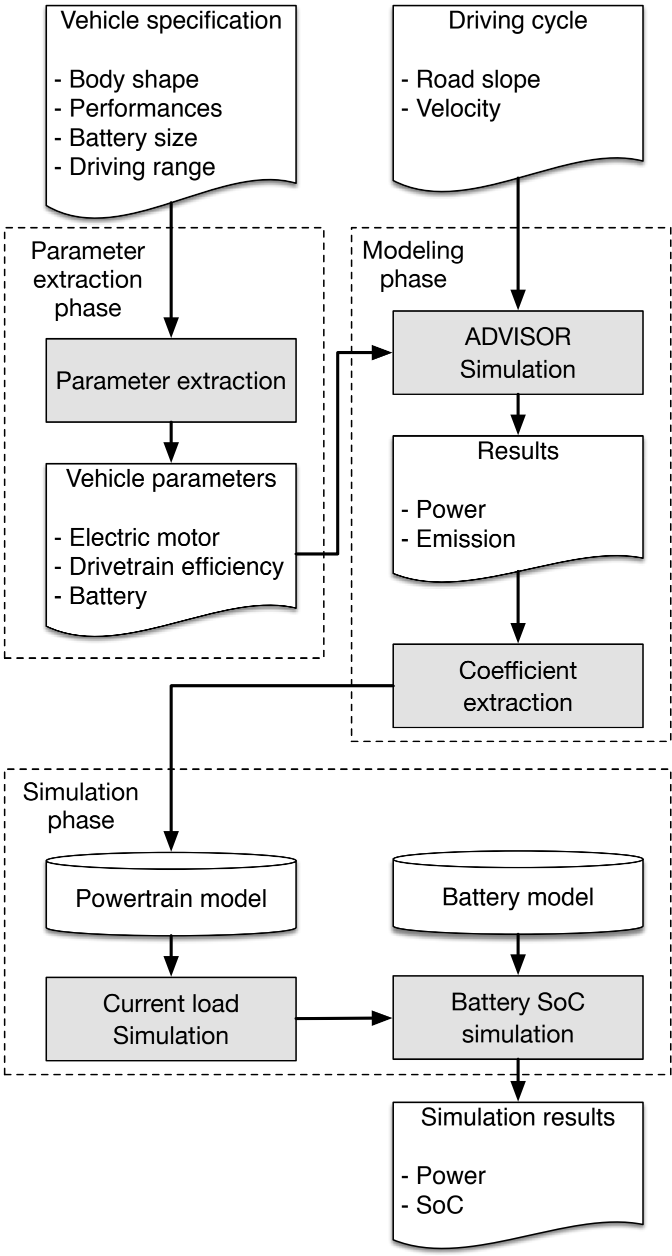


Figure 2. Overall process for the electric bus characterization.

by a given driving cycle promptly. We use the obtained power consumption to simulate the battery charging/discharging operation. The following Section III-C describes the details of battery SoC estimation.

C. Battery Pack Model

The EV battery pack typically includes a large number of Lithium battery cells. For example, a Tesla Model 3 battery pack consists of 444 Panasonic NCR18650B cells of 3,400 mAh nominal capacity with 74p6s arrangement. Hence, to model a pack, we need to model each individual cell, taking the load current and SoC variations of the usable battery capacity into account. This can be done with a circuit-equivalent model accounting for the capacity dependency on current magnitude and dynamics [19][20], as represented in Figure 3. The left-hand part of the circuit models the battery lifetime, with a capacitor C representing the battery storage capacity (Ah)

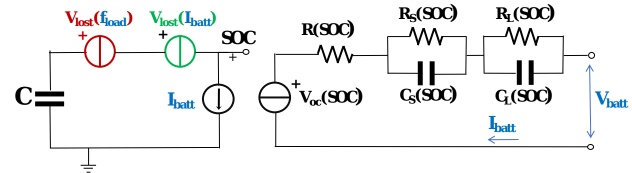


Figure 3. Circuit-equivalent model for battery cell [19].

and a current generator I_{batt} representing the battery current requested by the load. As the available capacity of the battery is affected by the load current values distribution, there are two voltage generators on the left part representing the dependency of the battery capacity (i.e., energy) on current values and the dependency on load current frequency, respectively. Both generators decrease the voltage at the SoC node (which represents the SoC) when either the current magnitudes or frequencies increase.

Starting from this model, we built a pack model by simply scaling parameters based on series/parallel connection. Besides its simplicity (e.g., cell mismatches are not considered) this is still a more realistic model than a linear one neglecting state-dependent information. Consideration of battery temperature is also a very important issue of battery SoC estimation. However, we leave the topic as a future work and focus on the state-dependent SoC estimation in this paper.

D. Driving Cycle Model

We extract a driving cycle, which represents a vehicle driving in a city. The driving cycle includes vehicle speed and road slope over time. We first extract a route to a destination and use related traffic information or rules and altitude information. We use speed limit and road traffic to synthesize the vehicle speed, whereas the altitude profile along the route is converted into road slopes. Figure 4 shows the road traffic and altitude of an example route from Google Maps [21] on the upper and lower subplots, respectively. Each color on the route means different levels of traffic: red means heavy traffic, orange means medium traffic, and blue means no traffic, respectively. We easily obtain the road slope from the change of altitude per distance unit.

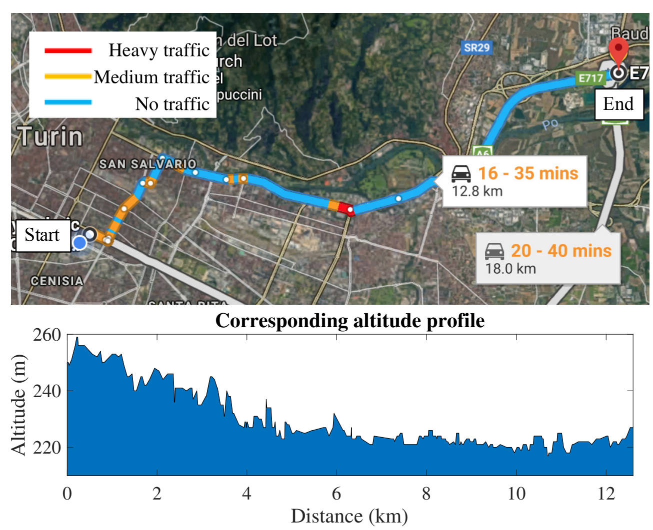


Figure 4. An example route on Google Maps [21] and its related altitude data.

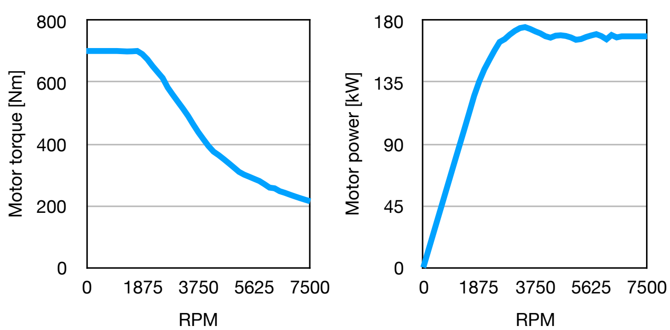
We do not consider the acceleration/deceleration occurring in correspondence to speed changes. Such approximation is not critical however, because the acceleration energy is small compared with the total energy consumption of each segment: acceleration/deceleration seldom last more than a few seconds.

IV. Simulation Results

We implemented a powertrain model of a BYD K9 bus from the vehicle specification and experiment results [4][22][23]. The gross vehicle weight of BYD K9 is 18,000 kg and the facial area of K9 is 2.55 by 3.36 m. K9 includes two electric motors whose maximum motor torque and power are 350 Nm and 90 kW, respectively. The motor type is in-wheel BYD-TYC90A Brushless Permanent Magnet Synchronous Motor. The maximum RPM is 7,500 and the gear box ratio is 17.7:1. The manufacturers unveiled the driving range of K9 as being an average 250 km, based on their experience. Battery size is 320 kWh and the maximum road slope to climb is 15%.

A. Vehicle Parameter Extraction

We used [24] to set the parameters of the electric motor that Larson transportation institute tested on the BYD electric bus more than eight months (from August 29, 2013 to May 13, 2014). The institute reported the maximum acceleration of the bus from stop: 4.8 s to 10 mph, 9.0 s to 20 mph, 16.2 s to 30 mph, 32.4 s to 40 mph and 47 s top speed (43 mph), respectively. We extracted (a) the maximum motor torque map and (b) the maximum motor power by RPM, with repeataed ADVISOR simulations, as shown in Figure 5.



(a) Maximum motor torque map. (b) Maximum motor power.

Figure 5. Motor parameter extraction results. (a) is the maximum motor torque map and (b) is maximum power map.

We specified the detailed vehicle parameters as indicated in Figure 6; this figure also shows the ADVISOR user interface for parameter extraction. The motor, together with the efficiency and battery models, are imported into ADVISOR, and based on the simulation results, we set the parameters so that the simulation results follow the experimental results. Figure 7 shows the difference between experimental results and simulation results of the driving range. We set the parameters for drivetrain efficiency to follow the trend of driving range by vehicle speed. There are about 200 km range difference between two lines respecting the experimental driving range and the simulation driving range in Figure 7. However, the range trend by the speed is similar enough. Also, the range difference is resolved by updating the battery model, as explained in the following section.

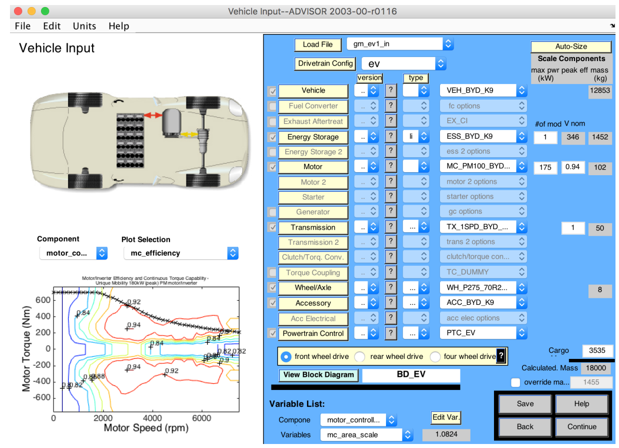


Figure 6. ADVISOR simulation setup.

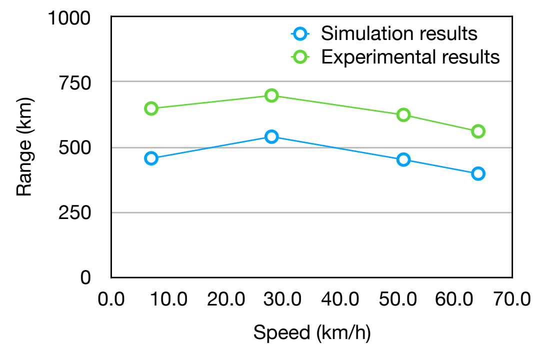


Figure 7. Driving range validation under efficiency parameter extraction.

B. Vehicle Powertrain Modeling

We extracted the coefficients of (1), (2) and (3) with a number of ADVISOR simulations. Table I summarizes the model coefficients of BYD K9. Figure 8 shows the difference between the estimation of power consumption by the vehicle simulator and the powertrain models; the normalized root-mean-square error is 9.12%.

TABLE I. MODEL COEFFICIENTS FOR BYD K9.

α	0.098	β	9.7562	γ	1.2016	δ	0.0001
C_0	1000.0	C_1	1378.2	C_2	0.00001	C_3	0.000015
ϵ	0.4095	ζ	2178.5				

C. Vehicle Simulation Setup

In our experiment, we followed the battery pack configuration provided by BYD to build our battery model. The battery is LiFePO4 (Lithium Iron Phosphate) with 540 V battery pack voltage. The battery pack consists of three battery modules and has 108 kWh capacity. We assumed that each battery cell in the pack is ideally balanced in the following experiments, then we built the battery pack model as indicated in Section III-A. Concerning the regenerative braking phase, we assume that charging efficiency is 20%, which means that 20% of the kinetic energy is converted to electric energy and transferred into the pack.

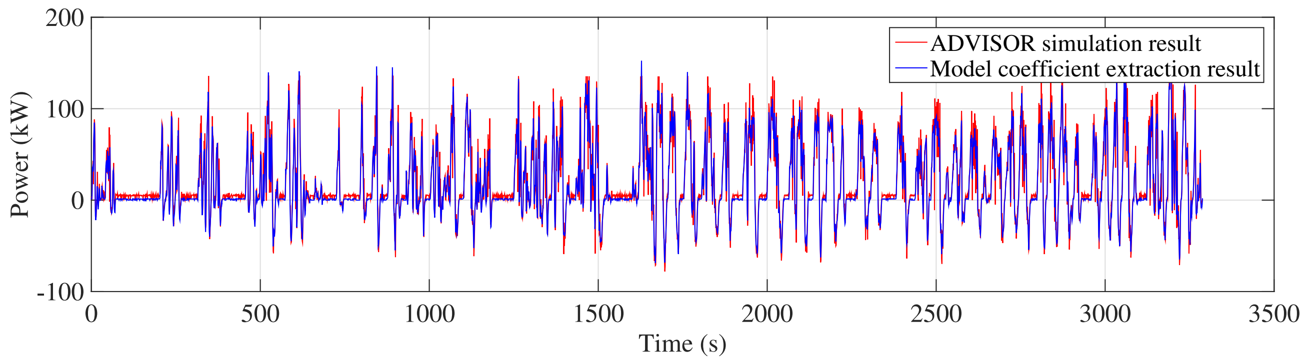


Figure 8. Powertrain model validation result.

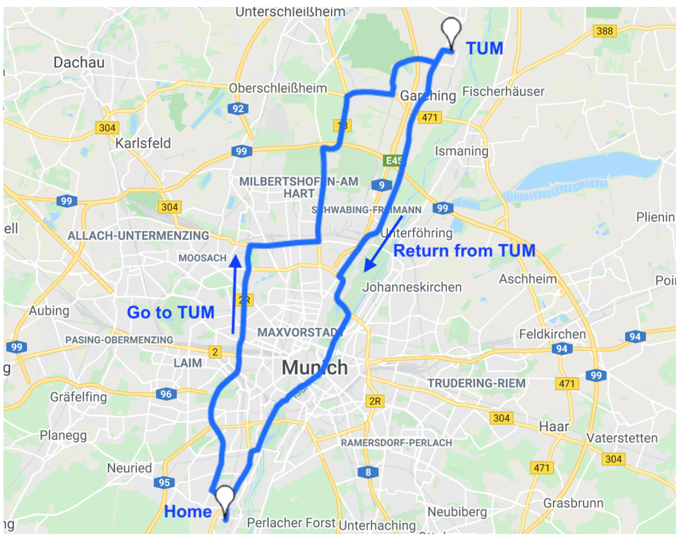


Figure 9. Routes from home to TUM and vice versa.

TABLE II. A ROUTE INFORMATION.

Route	Distance (km)	Avg. slope (degree)	Avg. speed (km/h)
Home to TUM	31.2	-0.1728	24.67
TUM to Home	26.2	0.2221	22.24

D. Case study 1: Fast Driving Energy Estimation

We extract a route going to Technische Universitat Munchen (TUM) and another one returning from TUM, as shown in Figure 9. Table II summarize the information of the routes: distance, average slope along the route and average vehicle speed.

The simulation results for the routes are shown in Figure 10. The first two graphs show the road altitude from home to TUM and the speed profile that we obtained from the road speed limit and the Google Maps traffic information. The third graph shows the corresponding power and energy consumption over time. The power consumption is low in the first half compared with the second half because the degree of negative slope along the road is high. Fourth and fifth graphs show the road altitude and speed profile from TUM to home. The sixth graph shows the power and energy consumption. The road slope is positive in this case. Therefore, the energy consumption is higher than the energy consumption to go to

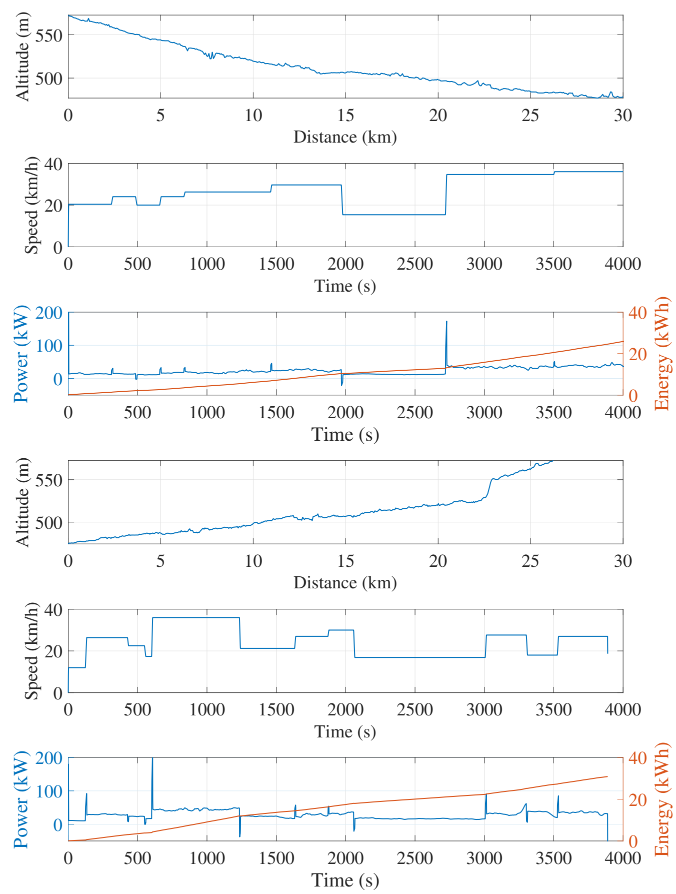


Figure 10. Simulation result from home to campus (first to third graphs) and from the campus to home (fourth to sixth graphs).

TUM. The driving distance going to TUM is longer than the route returning from TUM. However, the energy consumption to go to TUM (27.4 kWh) is nearly 10% lower than the energy consumption to return from TUM (30.8 kWh) because of the road slope. The proposed equation-form energy model helps us immediately estimate the energy consumption along the road, taking slope and traffic into consideration, and to decide which route is economic based on the fast simulation results.

E. Case Study 2: Battery Size Analysis

One important merit of the proposed power model is to estimate energy consumption in a short time, which is useful for iteration-based parameter sizing. For example, we can find

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the optimal battery size using iterative vehicle simulation. A short simulation time is mandatory in this approach. We perform the driving simulation on a flat 100 km distance with different battery pack sizes. We assume that the vehicle speed is 50 km/h, which is the average bus speed in the suburb of the city. We assume that the battery pack voltage is the same, and additional battery modules are attached in parallel. We assume that the battery pack is ideally balanced during battery charging and discharging.

We performed the vehicle simulations by changing the battery size from 70% of nominal battery size of BYD K9 to to 130%. Figure 11 shows the simulation results. As we increase battery size, the driving range also increases. However, the driving efficiency (energy consumption per unit distance) decreases because of the increase in battery weight. The driving range increases nearly 28% if we increase the battery size by 30%. On the other hand, the driving efficiency decreases up to 21%. Therefore, we should carefully decide the battery size with the consideration of cost of electricity per unit distance (efficiency) and bus service time (driving range with a fully charged battery).

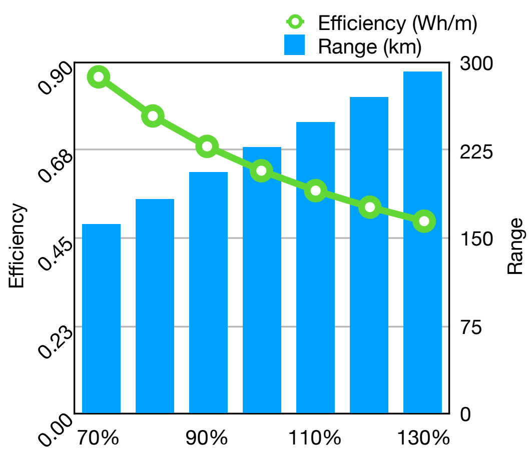

Figure 11. Simulation results by battery size.

V. Conclusion

We have proposed an improved EV range estimator incorporating (i) parameter extraction for complex EV simulation, (ii) equation-form powertrain modeling by coefficient extraction and (iii) fast vehicle energy simulation with a traffic- and altitude-aware driving cycle. We introduced two case studies as application of the proposed range estimator: (i) fast energy consumption estimation along the route information and (ii) bus battery sizing considering driving efficiency and range.

The estimator can work either offline, by estimating the range upfront without intermediate updates like a traditional GPS navigator, or online, refining the estimate at the cost of a route re-calculation. Our range estimator is meant as a "plug-in" for traditional or traffic-aware (e.g., Google Maps) GPS navigators, allowing route decisions besides traditional information based on travel time and route distance.

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