Pre-Estimation of Electric Vehicle Energy Consumption on Unfamiliar Roads and Actual Driving Experiments

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ABSTRACT

For this study, we constructed a system for pre-estimation of electric vehicle (EV) energy consumption on unfamiliar roads. Drivers of EVs must make plans based on estimated energy consumption because they fear that an EV might run out of power and stop on the road. Our constructed system pre-estimates ranges at which an EV can be expected to be forced to stop on a road. The range is calculated using EV driving simulation on a route that is input by a driver. The driving simulation requires only map data and the EV car specifications. Moreover, we assessed a system using a real EV. Results show that the system produced sufficiently correct ranges on the roads used for experimentation. Additionally, we evaluated the accuracy of ranges output by our system. For evaluation, we used numerous accumulated daily driving logs for EVs.

1. INTRODUCTION

In recent years, energy-efficiency and CO_2 emission reduction have become necessary worldwide because of climatic variation and scarcity of fossil fuels. Given that background, electric vehicles (EVs) are attracting global attention. Reportedly, EVs present the benefit that so-called well-to-wheels CO_2 emissions are lower than those of internal combustion vehicles (ICVs). In addition, EVs have no emissions when they are running. Many countries have formulated EV deployment goals for the future. Therefore, EVs are expected to penetrate markets gradually worldwide.

Nevertheless, many difficulties arise when a user operates an EV. One is the difficulty of EV travel planning when a user navigates unfamiliar roads. Planning must be done while considering an EV travel range and when and where one might stop at a charging station. However, EV travel ranges change drastically because of road gradients and traffic conditions. Therefore, average users have difficulty making a precise plan for unfamiliar routes.

As described in this report, we propose a system that supports an EV user's travel planning on unfamiliar roads. We present a solution for pre-estimating the EV energy consumption range: minimum energy consumption E_{min} and maximum energy consumption E_{max}. We present E_{min} and E_{max} to assist planning. In addition, if E_{min} and E_{max} are correct, actual energy consumption E_{real} is in the range of E_{min} – E_{max}. Therefore, to evaluate the accuracy of the proposed system, we conducted EV driving experiments on roads with two conditions and confirmed that E_{real} is in the range of E_{min} – E_{max}.

2. RELATED WORKS

Studies of many types have estimated EV energy consumption and therefore the EV travel range. Using a motion equation model and actual driving logs collected by a probe car, most of these studies have produced methods to calculate EV energy consumption or travel range. Grubwinkler et al. estimated EV energy consumption from statistical analysis of driving data generated from large amounts of collected driving data[5]. Ito et al. estimated EV travel ranges from averaging energy consumption maps from a probe car database[6]. Zhang et al. proposed estimation of EV travel range using driving logs, traffic conditions, and weather[12]. Styler et al. proposed a means of controlling a Range EXtender (REX) EV more efficiently using estimated energy consumption generated from probe car data[9]. Yang et al. proposed a means of estimating energy consumption and CO_2 emissions from average speed and stop frequency data acquired by passage sensors at an intersection[11].

Moreover, many studies have solved optimization problems of energy consumption and driving using motion equations and other data. Karbowski et al. proposed a means of controlling plug-in hybrid EVs (PHEVs) using an energy consumption simulation generated from traffic, road maps, and Markov Chain[7]. Kurtulus and Inalhan proposed a route decision algorithm for REXEV considering energy consumption calculated from traffic, weather, maps, and the destination[8]. De Souza et al. proposed a traffic assignment algorithm that minimizes EV travel time and energy consumption[1]. Felipe et al. estimated energy consumption using an artificial neural network into which driving styles and route features are input[4]. Fei et al. proposed hybrid models incorporating a motion equation model and a machine learning model[3]. Unlike these studies, we make our contribution by evaluating the practicality of our system using large amounts of data acquired in different regions.

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Table 1: Variables of Expression (1)

Variable	Unit	Meaning	How to get
g	m/s^2	gravitational acceleration	constant
ρ	kg/m^3	air density	constant
μ	-	rolling resistance coefficient	constant
C_d	-	air resistance coefficient	car specification
A	m^2	face area of the vehicle	car specification
M	kg	mass of the vehicle	car specification
M_i	kg	inertia mass of the vehicle	car specification
α	rad	road gradient	map data
v	m/s	velocity	constant speed is set
η	-	conversion efficiency	car specification

3. PRE-ESTIMATION SYSTEM

To pre-estimate EV energy consumption, the EV user inputs only an origin and a destination and anticipated stop locations (sightseeing spots or stores, etc.) during a trip. Next, the system generates origin-destination (OD) trip simulation logs running on candidate routes at a constant speed v_c from these inputs. Trip simulation logs are normalized by time. We set speed v_c in advance, for example, a speed limit on a road.

Then, trip simulation logs are input to an EV energy consumption model. We use a model based on a motion equation[2]. Then E_{min} and E_{max} are calculated from outputs of the EV energy consumption model.

3.1 E_{min} Calculation

This subsection presents a description of minimum energy E_{min} calculation. For this report, E_{min} is defined as "energy consumption when an EV runs at constant speed v_c and does not stop."

First, an EV energy consumption log is calculated every second by inputting a trip simulation log into the EV energy consumption model. Expression (1) represents the EV energy consumption model. Table 1 presents variables of Expression (1), in which c represents $1/3600/1000$ J/kWh, and t denotes a time.

$$e_t = c((\frac{1}{2}\rho C_d A v^2 + \mu M g \cos\alpha + M g \sin\alpha + (M + M_i)\frac{dv}{dt}) \times \frac{1}{\eta} \times v) \quad [kWh] \tag{1}$$

Finally, $E_{\min}$ is calculated as the summation of e_t (Expression (2)). Also, n represents the number of simulation logs of an OD trip.

$$E_{\min} = \sum_{t=0}^{n} e_t \quad [kWh] \tag{2}$$

3.2 E_{max} Calculation

This subsection presents our description of how to calculate maximum energy E_{max}. We define E_{max} as "energy consumption when an EV runs at constant speed v_c, and accelerates and decelerates when stopping at every stop location and every signal, assuming bad conversion efficiency during acceleration and deceleration."

Therefore, we define E_{max} as shown in Expression (3) because we want to express it easily. E_{acc} is described in Expression (4). Additionally, N stands for the number of stops when an EV stops at every stop location and every signal.

$$E_{max} = E_{min} + E_{acc} \quad [kWh] \tag{3}$$

$$E_{acc} = N \times \frac{1}{2}(M + M_i)v_c^2 \times \frac{1}{\eta} \quad [kWh] \tag{4}$$

In E_{acc}, we consider two situations. First, an EV makes no gains from kinetic energy through regenerative braking when slowing the vehicle. Second, we chose $\eta = 0.7$ empirically for estimating the worst conversion efficiency.

Table 2: Experiment Trips

Route ID	Distance	Type	Charging Spot
kitami_1	163 km	Long	121 km point
kitami_2	126 km	Long	67 km point
kitami_1'	163 km	Long	85 km point 121 km point
outward	27 km	Short	do not care
homeward	24 km	Short	do not care

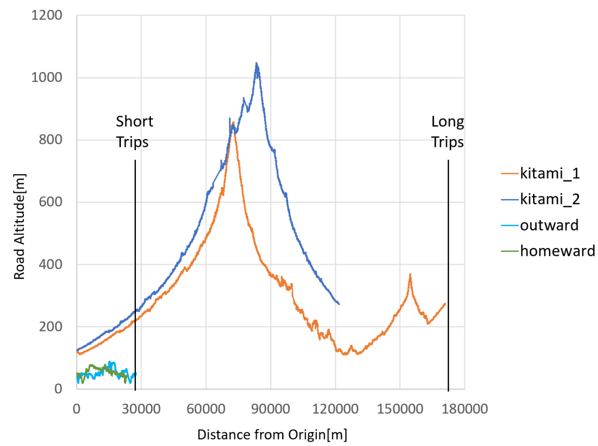

Figure 1: Altitude and Distance of Experiment Trips.

4. EXPERIMENT

This section presents comparison of E_{min} and E_{max} with E_{real}. The actual energy consumption was E_{real} for our experiment. We used trips of two types for experimentation: long trips and short trips (Table 2). Figure 1 presents the altitude and distance of experiment trips. We ignored charging spots on short trips because the trip distance is sufficiently short that additional charging is not required.

4.1 Long trips

4.1.1 Experiment conditions

We conducted EV driving experiments for long trips in Hokkaido in 2017 and 2018. Hokkaido has an area that

Figure 2: Experiment Routes in Hokkaido in 2017.

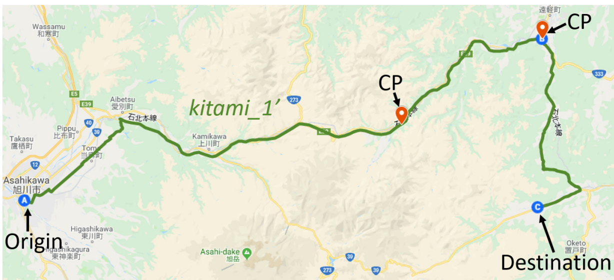

Figure 3: Experiment Routes in Hokkaido in 2018.

is the longest interval in Japan between charging stations. In this area, a fundamental problem arises of whether an EV can arrive at the next charging station after it leaves a charging station. Therefore, we conducted experiments on three routes to ascertain which route is best for an EV driver.

We simulated $kitami\_1$ and $kitami\_2$ using the system in 2017. Figure 2 shows $kitami\_1$ and $kitami\_2$ routes. We designated charging points as CPs. The $kitami\_1$ travel distance is greater, but the elevation difference is smaller. Furthermore, the $kitami\_2$ travel distance is shorter, but the elevation difference is greater. We simulated $kitami\_1'$ in 2018 (Fig. 3) because a new charging station is located there.

4.1.2 Experiment results

Table 3 shows the pre-estimated results. We conducted EV driving experiments using a Nissan Leaf (Nissan Motor Co. Ltd.) as the experiment EV in 2017 and 2018. We used estimated energy consumption logs[10] calculated from GPS data as E_{real}. In 2017, the experiment EV's remaining battery charge was the equivalent of 13.4 kWh when its battery was 80% charged. That charge was achieved through charging time of 30 min. We selected and ran $kitami\_2$ because $kitami\_1$ E_{min} was 15.27 kWh (greater than the 13.4 kWh @80%), as Table 3 shows. These calculations indicate that the EV can run the whole $kitami\_1'$ route if the remaining battery charge is greater than 15.01 kWh. The experiment EV was 16.7 kWh @100% (more than 15.01 kWh). Therefore, we chose the $kitami\_1'$ route for the 2018 experiment. Table 4 shows E_{real} for the actual driving experiments. We can infer that the system outputs "E_{min} and E_{max}" are correct because E_{real} is between E_{min} and E_{max}.

4.2 Short trips

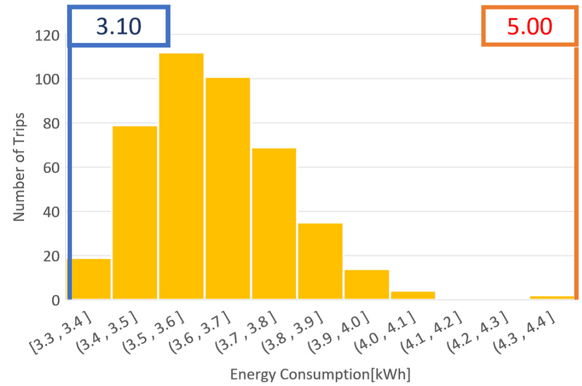

Figure 4: E_{real} in Outward Trips.

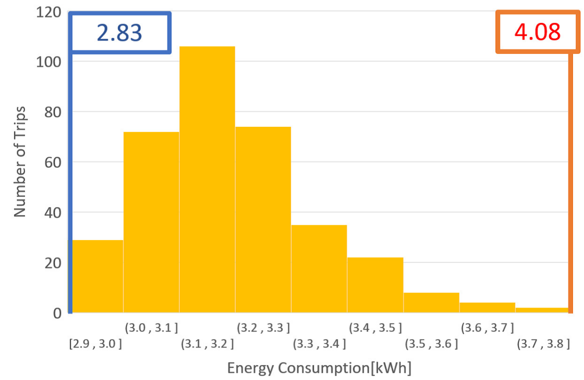

Figure 5: E_{real} in Homeward Trips.

4.2.1 Experiment conditions

After we accumulated EV energy consumption logs[10] in a database, we evaluated the accuracy of E_{min} and E_{max} using EV energy consumption logs accumulated from daily commuting. We therefore accumulated a large amount of one commuter's data. The total number of trips was 786: outbound trips were 434, homeward trips were 352. Therefore, we use these logs as E_{real}. We then compare E_{min} and E_{max} with E_{real} to evaluate their accuracy.

4.2.2 Experiment results

Table 5 presents pre-estimated results. Figures 4 and 5 portray histograms of E_{real} values. These graphs show that any E_{real} values are always between E_{min} and E_{max}.

4.3 Overall experiment results

As shown in Figure 6, we verified that any E_{real} values are always between E_{min} and E_{max}, even though EVs run on long trips or short trips. E_{real} of *outward* and *homeward* are mean values of numerous accumulated trips.

5. CONCLUSION

As described in this report, we proposed a system for pre-estimation of maximum and minimum electric vehicle (EV) energy consumption for use with unfamiliar roads. We defined the minimum energy consumption is achieved when an

Table 3: E_{max} and E_{min} in Long Trips

Route ID	Origin to CP E_{max}	Origin to CP E_{min}	CP to next CP E_{max}	CP to next CP E_{min}	CP to Destination E_{max}	CP to Destination E_{min}
kitami_1	19.17 kWh	15.27 kWh	-	-	6.62 kWh	5.88 kWh
kitami_2	12.20 kWh	9.18 kWh	-	-	5.95 kWh	5.75 kWh
kitami_1$'$	15.01 kWh	11.98 kWh	4.16 kWh	3.29 kWh	6.62 kWh	5.88 kWh

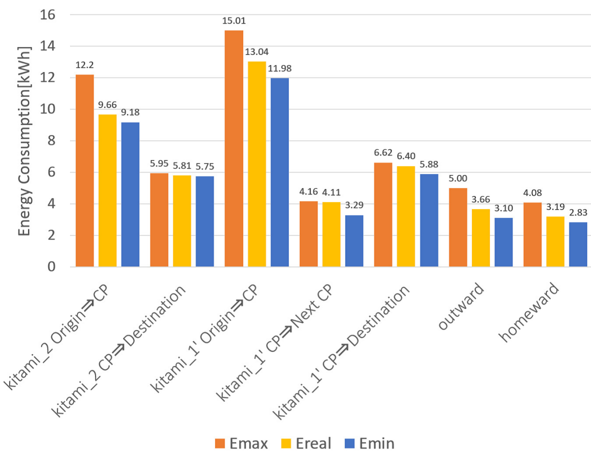

Figure 6: Overall Experiment Results.

Table 4: E_{real} on Long Trips

Route ID	Origin to CP E_{real}	CP to Next CP E_{real}	CP to Destination E_{real}
kitami_2	9.66 kWh	-	5.81 kWh
kitami_1$'$	13.04 kWh	4.11 kWh	6.40 kWh

Table 5: E_{max} and E_{min} in Short Trips

Route ID	E_{max}	E_{min}
outward	5.00 kWh	3.10 kWh
homeward	4.08 kWh	2.83 kWh

EV travels at a constant speed. Maximum energy consumption occurs when an EV travels at a constant speed, but also stops at controlled intersections and set places, such as sightseeing spots and stores.

Moreover, we conducted actual driving experiments, which yielded actual energy consumption logs with data in a range showing the estimated minimum energy consumption and estimated maximum energy consumption. Our next challenge is to estimate a range that is specialized for individuals and routes using numerous daily life logs. Another challenge is consideration of an air conditioner's energy consumption to output more correct EV energy consumption.

6. ACKNOWLEDGMENTS

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