Estimation of EV Power Consumption and Route Planning Using Probe Data

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Against the global backdrop of increasingly strict fuel regulations, the number of electrical vehicles (EV) is expected to rise dramatically. However, EVs have less mileage than gasoline vehicles. While efforts have been made for the improvement of battery performance, we also use different approaches to this issue. In this study, we developed an engine that can estimate EV power consumption by building a model formula corresponding to the characteristics of each road link. To devise this formula, a distributed processing platform was adopted. We also developed an application platform that supports route planning by providing the drivers with information about power consumption and battery charging stations. These developments will contribute to the creation of a sustainable society by promoting the use of EVs and reducing CO_2 emissions.

Keywords: electric vehicle (EV), power consumption estimation model, probe

1. Introduction

Recently, electric vehicles (EVs) have been gaining in popularity as eco-friendly vehicles with more and more people concerned about the environment. By law, carbon dioxide (CO_2) emissions from cars must be reduced to below 95 g/km by 2020 in Europe(1) and EV technology is becoming increasingly important. Automotive manufacturers are reducing gas vehicle production and are promoting the sale of EVs and hybrid vehicles (HVs). EVs will be common in the near future.

However, the driving distance of EVs is shorter than that of gas vehicles. Various solutions have been taken to the problem besides the improvement of the battery performance. For example, one approach is the estimation of power consumption in a vehicle navigation system, while another approach is to supply services in order to reduce the anxieties of people.

In the case of estimation of power consumption, the power consumed by an EV is affected by several factors: car-mounted devices like an air conditioner, road conditions, etc. In addition, an EV has regenerative braking capability. When an EV runs on a downhill slope, the motor generates power and the battery is charged. Most EVs have indicators for remaining battery levels and drivers can approximately estimate how far they can keep driving. However, the consumed power fluctuates because of the above factors. We need to estimate the situational variation of power consumption. Various kinds of data storage and analysis are needed for the exact estimation. Collecting vehicle data by using probe cars is a suitable method. Yet, the data amount increases along with the growth in the number of EVs. The huge amount of data must be analyzed efficiently and timely.

Regarding supplied services, we should reduce the driver's anxieties to promote the use of EVs, and one solution is through the use of the intelligent transportation systems (ITS). Their anxieties will be removed if they can grasp information such as how far their vehicles can go without recharging, or where they should charge their vehicles through the telematics service. In the telematics field, smartphone applications for car navigation have recently become popular in addition to the traditional car navigation systems which are permanently integrated into the vehicle. Since they can be used not only inside of cars but also outside of cars, such as home or office, they seem to be more suitable for providing information about routes for EVs.

In this study, we have focused on the factors that affect power consumption, running resistance (rolling friction), air gradient, and regenerative energy. We have built a model formula between the consumed power, running resistance, and regenerative energy. We have calculated the formula coefficients by using the machine learning method. We have estimated the consumed power of a vehicle in each road link. We have compared the calculation values with the actual driving car data and evaluated their validity. We have used the car prove data to learn the model formula. We have calculated and analyzed the data on the distributed processing platform "Hadoop."

We have also studied and developed several services to calculate and provide the information about route planning for EVs, and developed an application platform to provide them as smartphone applications. We describe the outlines of our application platform for EV route planning.

2. Structure of EV Route Searching Service

Figure 1 is an image of the route searching service which includes an EV power consumption estimation engine on a distributed processing platform. The estimation engine calculates the power consumption of each link, and the service shows the minimum power consumption route to drivers.

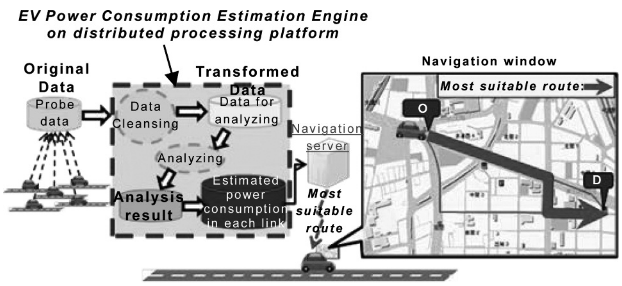

Fig. 1. Image of route searching service with EV power consumption

We estimate power consumption by using the following procedures:

(1) Preprocess and reform of the probe information (original data) gathered from the EV to adequate data (transformed data) in each link.
(2) Analyze the Transformed Data and build the model formula (analysis result) in each link.
(3) Estimate the EV power consumption in each link.

The analysis results are model formulas in each link, which are basic information to estimate the power consumption.

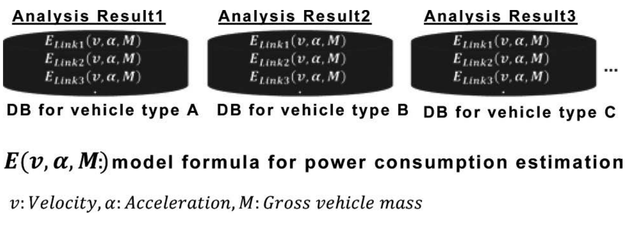

Fig. 2. Image of analysis results

2-1 Model formula

It is noted that the power consumption of a vehicle depends on driving force, power train transmission efficiency (η(*eta*)), and motor-controller efficiency (ε(*eplilon*)).

Driving force is equal to the sum of four kinds of vehicle resistance – air resistance (R_{air}), rolling resistance (R_{roll}), slope resistance (R_{slope}), and acceleration resistance (R_{acc}). The motor of a vehicle outputs the driving force (F_d) to balance these four types of resistance.

We constructed the basis for the model formula (P) considering these parameters (**Fig. 3**).

■ **Power consumption dependency**

$P(v, \alpha, M)$ .... depend on $\begin{cases} F_d = R_{air} + R_{roll} + R_{slope} + R_{acc} \\ \text{and} \\ \eta, \varepsilon \end{cases}$

Basis for model formula

F_d: Driving force, R_{air}: Air registance, R_{roll}: Rolling registance, R_{slope}: Slope registance, R_{acc}: Acceleration registance, η: Power train transmission efficiency, ε: Motor – Controller efficiency

■ **The amount of power consumption per unit time**

$$E_{acc} = \int P\,dt(W \cdot s) \quad (F_d \geq 0) \quad (1)$$:Model formula for acceleration

$$E_{acc} = \int P\,dt \cdot \phi(W \cdot s) \quad (F_d < 0) \quad (2)$$:Model formula for deceleration

ϕ: Recovery efficiency of regeneration energy

Fig. 3. Image of model formula

3. Evaluation of Estimation Engine

In this section, we describe the evaluation result of the estimation engine with the model formula. The first thing that we tried to do was to evaluate the model formula. After we concluded that the parameters of the model formula were effective, we evaluated the estimation engine. We tested the following items to develop the EV power consumption estimation engine.

(1) Estimation of the recovery efficiency of regenerative energy (ø)
(2) Verification of the validity of the model formula
(3) Verification of the validity of the power consumption estimation engine

We verified an EV power consumption estimation engine by using an EV whose maximum output is 47 kW, weight is 1080 kg, and battery capacity is 16 kW. We performed a driving test from September to October 2012 using the EV. The total driving time was 150 hours.

3-1 Estimating the recovery efficiency of regenerative energy (ø)

We must consider the recovery efficiency of the regenerative energy to estimate the amount of power consumption, because EVs have a regenerative energy mechanism which transforms the energy accumulated by acceleration into regenerative energy when the vehicle decelerates.

This time we estimated the recovery efficiency of the regenerative energy of each EV by using accumulated probe data.

Figure 4 shows the calculated results. The vertical axis shows the recovery efficiency of the regenerative energy, and the horizontal axis shows the velocity zone. The results show every driving mode. The driving modes are Drive, Eco, and Brake modes.

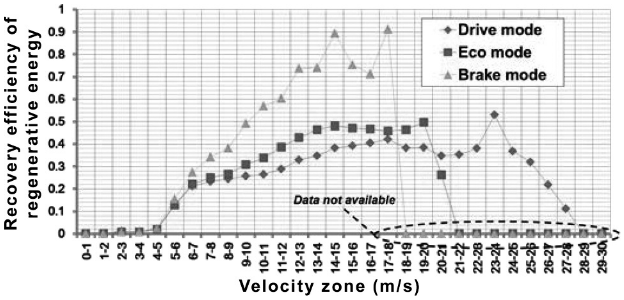

Fig. 4. Recovery efficiency of regenerative energy

From the results, the recovery efficiency of the regenerative energy rises with velocity. Moreover, at 0–5 m/s velocity zone, energy does not regenerate for most points.

We confirmed the recovery efficiency of the regenerative energy for every velocity zone.

3-2 Verifying the validity of the model formula

To verify the validity of the model formula, we evaluated each link with the accumulated probe data. We compared actually measured power consumption and estimated power consumption with the model formula, per unit time.

Figure 5 shows the evaluation results verifying the validity of the model formula. On the left side, the graph shows the rate of correlation coefficient for the acceleration of the vehicle. On the right side, the graph shows the rate of correlation coefficient for the deceleration of the vehicle. The average correlation coefficient at acceleration (cruising) was 0.87, and the average correlation coefficient at deceleration was 0.77.

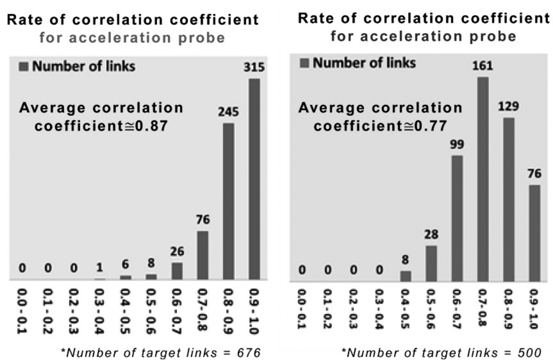

Fig. 5. Evaluation results of verified validity of model formula

The results show that the parameters of the model formula were effective.

3-3 Verifying the validity of the power consumption estimation engine

To verify the validity of the estimation engine, we evaluated the accumulated probe data. We defined "TRIP" as probe data divided by 10 km, and then we evaluated the margin of error between the estimated power consumption and actually-measured power consumption for each TRIP.

The number of TRIP to be evaluated is 6,557. We calculated the precision by using one-leave-out cross validation. We used **formula (1)** as the evaluation index. "Pc" is precision, "Mv" is actually measured power consumption, and "Ev" is estimated power consumption. The larger the value is, the more accurate the estimation is, which means that estimated power consumption is close to actually-measured power consumption.

$$P_c = \left(1 - \frac{|M_v - E_v|}{M_v}\right) \times 100\ (\%) \quad (P_c \leq 100) \qquad (1)$$

P_c: *precision*, M_v: *actual measured value*, E_v: *estimated value*

Table 1 shows the evaluation results.

Table 1. Evaluation result of estimated power consumption

TRIP average precision (%)	TRIP maximum precision (%)	TRIP minimum precision (%)
88.4	99.9	47.3

Moreover, by extracting the typical TRIP from different groups, we evaluated the precision of estimated power consumption per unit distance. **Figure 6** shows the evaluation results.

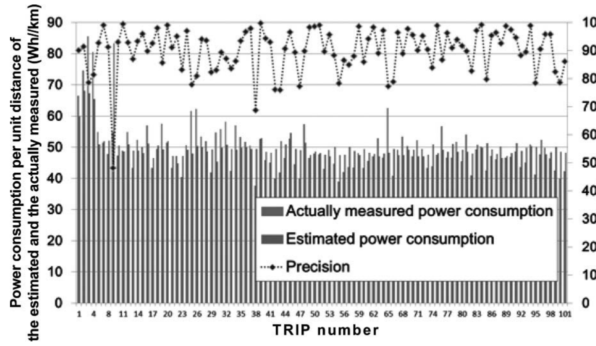

Fig. 6. Evaluation results of the estimated power consumption per unit distance

Although the average precision is 88.4 percent, there are links whose precision is not high. We analyzed the low precision links and we found the following reasons:

a) The probe data in the link non-uniformly-exists.

b) Power consumption varies widely at the same velocity zone.

In case a), we can clear the problem by gathering more probe data. In case b), we conclude that the traveling pattern wields influence over power consumption. In the future we will estimate the traveling pattern.

4. The Application Platform for EV Route Planning

Our application platform consists of a client application, which is a smartphone application for car navigation, and a server application, which executes route planning. The client has a map display function, location detection function, route planning function, route guidance function and facility search function. It requests and obtains road map data, route data, facility data and traffic information to realize these functions. The server receives requests from the client, generates required data and sends it to the client. In the client, route planning requests are received and it outputs information for EV route planning, and the route planning engine in the server calculates it. The route planning engine uses road network data, real-time traffic information and predicted traffic information to calculate an ordinary route, and it additionally uses road slope data and charging station information to calculate a route for an EV (**Fig. 7**).

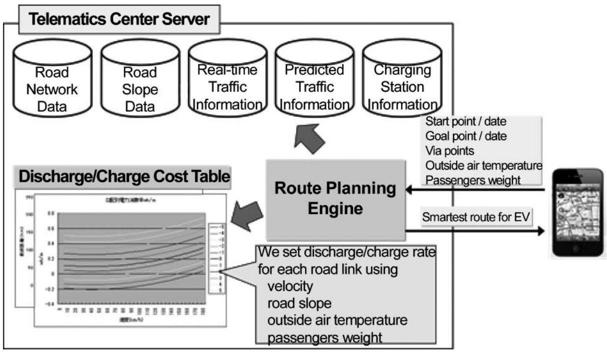

Fig. 7. System overview of the application platform for EV route planning

We have studied what types of information are useful for EV users, and have developed three types of EV route planning functions. In this section, we describe these functions.

(1) Conditions for EV Route Planning

First of all, we describe the conditions for EV route planning. The following parameters are required to be set to calculate precise EV route planning (**Fig. 8**).

a) Number of passengers

The electric energy consumption of a vehicle is a function of vehicle mass, which is affected by the number of passengers.

b) Air temperature

The air temperature affects the electric energy consumption of a vehicle in various ways, for example, by use of an air conditioner.

c) Charge in the battery at the origin

The charge in the battery at the origin is required to calculate various information for EV route planning.

d) Charge in the battery at the destination

When you can charge near the destination, you need not worry about how much charge is left in the battery at the destination, but when you cannot, you need to pay attention to leave some charge in the battery at the destination to be ready for the next drive. This is the reason why this parameter is required to be set.

e) Depth of charge and discharge

It is preferable that the charge in the battery is kept within a certain range since over discharge and over charge damage and shortens the life of the battery. The depth of charge and discharge are thus required to be set. The server plans a route wherein the driver can access a charging station before the charge in the battery drops below the depth of discharge, and it is then charged to the depth of charge.

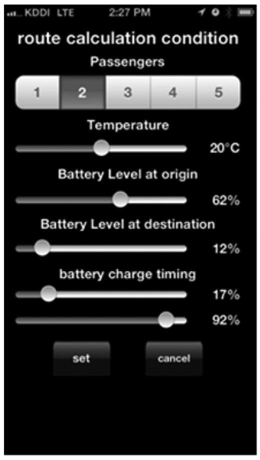

Fig. 8. User interface for setting conditions for EV route planning

(2) Arrival Zone Map Search Function

For EV users and those who consider using it, it is useful to know how far an EV can cruise without recharging from the origin such as their homes. The arrival zone map search function, which we have developed, provides this information. An arrival zone is a set of roads on which an EV can arrive without recharging. Our arrival zone map search function finds the arrival zone of an EV for a given origin. On the client, roads in the arrival zone are displayed on a map in multiple colors corresponding to the level of remaining battery charge on them. **Figure 9** shows an example of the arrival zone map. With a map like **Fig. 9**, you can easily understand electric energy required to drive from an origin to any point, which is very useful, particularly when you are planning where to travel by your EV next holiday.

Fast computation and easy to see visualization are challenging subjects in the arrival zone map search. It is clear that an EV can cruise roads near the origin without recharging. Based on this fact, our algorithm searches only major roads in an area near the origin and all roads, including minor roads, outside of the area. Thus we have succeeded in the reduction of the computational time and the creation of an easy to see arrival zone map.

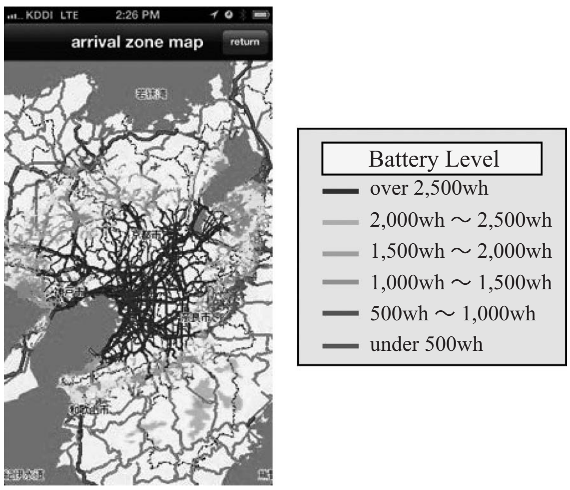

Fig. 9. Arrival zone map

(3) Optimum Route and Charging Stops Planning Function

Suppose that you are going to drive to a destination, and you have to charge on the way to the destination. It is important to find a charging station to minimize the duration to the destination. This becomes more complex when you need to charge several times. As we described in (1), there are a lot of things to consider when charging an EV. Our optimum route and charging stops planning function finds the most economical route from an origin to a destination that visits one or more charging stations if necessary, while considering the charge in the battery at the origin as well as a target charge to be left, the depth of charge, and the depth of discharge at the destination. It uses quantities, such as the time, the distance, the energy consumption or a weighted sum of them, as the cost to minimize. Our algorithm evaluates candidates of charging stations to visit so efficiently that it can find the optimum route quickly enough even when the number of charging stations is large and more than one charge is required. **Figure 10** shows an example of an optimum route and charging stops planning.

Fig. 10. Optimum route and charging stops planning

(4) Power Consumption Estimation Function

How much charge is left in the battery is one of the pieces of information which EV users care about while they are driving. While an EV is running, the charge in the battery is not only consumed and reduced, but also recharged and increased by the regenerative braking energy during braking or driving down slope. Consider the case where you are driving an EV and there is a hill on the way to the destination. When you are running on the up slope of the hill, the battery charge becomes low. If you have no information in advance, you may feel uneasy that the battery may be dead before arriving at the destination, even if it will recover enough to arrive at the destination during the down slope. If you comprehend the electric energy consumption including the regenerative braking energy and battery charging level at every point on your route, you can feel confident to drive to the destination.

Our power consumption estimation function estimates energy consumption of an EV and the level of charge in the battery at every point on the route planned by the optimum route and charging stops planning function. The server estimates this data, and the client visualizes it as power consumption charts. **Figure 11** shows power consumption charts for the route shown in **Fig. 10**. In **Fig. 11**, the altitude, total energy consumption from the origin, and level of charge in the battery are drawn in different color lines, respectively, and those of the section which the vehicle has run are drawn in deeper colors. You can thus easily comprehend energy consumption and the level of charge at any point at a glance.

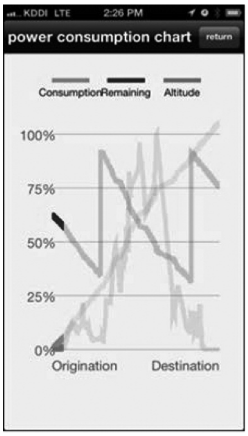

Fig. 11. Power consumption charts

5. Conclusion

In this paper, we present the EV power consumption estimation engine and application platform for EV route planning. We have especially focused on three EV route planning functions. The arrival zone map search function is helpful for people who consider using EVs to understand the performance of them. The optimum route and charging stop planning function and the power consumption estimation function are helpful for people who are driving EVs.

We believe that our application platform will contribute to the creation of a sustainable society by helping to increase the use of EVs and thereby reduce the emissions of CO_2 and other greenhouse gases.

· Hadoop is a trademark or registered trademark of Apache Software Foundation

Reference

(1) "Road transport: Reducing CO_2 emissions from vehicles," http://ec.europa.eu/clima/policies/transport/vehicles/index_en.htm (30th Jul. 2012)

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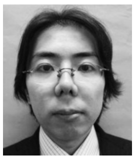

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