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Exploring the interactive effects of ambient temperature and vehicle auxiliary loads on electric vehicle energy consumption

Kai Liu[a,*], Jiangbo Wang[a], Toshiyuki Yamamoto[b], Takayuki Morikawa[c]

[a] School of Transportation and Logistics, Dalian University of Technology, No. 2 Linggong Road, Ganjingzi District, Dalian 116024, China
[b] Institute of Materials and Systems for Sustainability, Nagoya University, Furo-cho, Chikusa-ku, Nagoya 464-8603, Japan
[c] Institute of Innovation for Future Society, Nagoya University, Furo-cho, Chikusa-ku, Nagoya 464-8603, Japan

HIGHLIGHTS

- The effect of ambient temperature on EV energy consumption is modelled.
- The interactive effects of ambient temperature and auxiliary loads is explored.
- Energy consumption of the heater during warm conditions is conventionally exaggerated.
- Energy consumption of air conditioner during cold days is typically underestimated.
- Eradicating unreasonable EV auxiliary loads yields an average savings of 9.66% per km.

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ABSTRACT

The ability to accurately predict the energy consumption of electric vehicles (EVs) is important for alleviating the range anxiety of drivers and is a critical foundation for the spatial planning, operation and management of charging infrastructures. Based on the GPS observations of 68 EVs in Aichi Prefecture, Japan, an energy consumption model is proposed and calibrated through ordinary least squares regression and multilevel mixed effects linear regression. Specifically, this study focuses on how the ambient temperature affects electricity consumption. Moreover, the interactive effects of ambient temperature and vehicle auxiliary loads are explored. According to the results, the ambient temperature affects the energy efficiency significantly by directly influencing the output energy losses and the interactive effects associated with vehicle auxiliary loads. Ignoring the interactive effects between ambient temperature and vehicle auxiliary loads will exaggerate the energy consumption of the heater during warm conditions and underestimate the energy consumption of the air conditioner during cold conditions. The most economic energy efficiency was achieved in the range of 21.8–25.2 °C. The potential energy savings during proper usage of vehicle auxiliary loads is discussed later based on estimated parameters. As a result, a mean of 9.66% electricity will be saved per kilometre by eradicating unreasonable EV auxiliary loads.

1. Introduction

To reduce the dependency on fossil fuels and creation of harmful emissions, electric vehicles (EVs) have attracted significant attention in recent years [1,2]. Nevertheless, the driving range of EVs is not competitive compared to that of internal combustion engine vehicles due to significant technological barriers. These barriers make drivers feel anxious about the remaining energy. Accurate range prediction is the key to minimizing range anxiety and helping drivers make the best use of their available energy [3,4]. More importantly, vehicle energy consumption is a critical factor considered in both the transportation planning process and the evaluation of the energy impacts of operational-level projects [5], especially in the spatial planning, operation and management of charging infrastructures.

According to previous studies, a variety of factors affect energy consumption, including travel-related factors [6,7] (such as travel distance, velocity, acceleration, and cruise time), environment-related factors [8–12] (such as ambient temperature, visibility, and wind effects), vehicle-related factors [12–14] (such as vehicle mass and weight; vehicle auxiliary loads for heating, ventilation and air conditioning), roadway-related factors [15,16] (such as road gradients and other factors), traffic-related factors [17,18] (such as traffic conditions, the

* Corresponding author.
E-mail addresses: liukai@dlut.edu.cn (K. Liu), wangjiangbo@mail.dlut.edu.cn (J. Wang), yamamoto@civil.nagoya-u.ac.jp (T. Yamamoto), morikawa@nagoya-u.jp (T. Morikawa).

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probability of an interruption caused by a traffic signal, traffic control or pedestrian) and driver-related factors [19–22] (such as driving behaviours, car-following behaviour and charging habits). Moreover, the health and degradation conditions of the battery [23–27], the efficiency of braking energy recovery [28–32] and the prediction error of the current state of charge (SOC) of the battery [33] are characteristic factors that affect the energy efficiency of an EV.

Most previous studies have ignored the factors related to the environment because of the difficulty associated with data collection and impact quantification. However, environment-related factors, especially the ambient temperature, have significant effects on EV energy consumption. A few studies have focused on the performance of vehicle batteries under the influence of ambient temperature [8–12], and the authors attempted to solve the problems that batteries encounter at extremely low temperatures [34]. However, the authors neglected the complicated variation characteristics of the influence of temperature on energy consumption. Some reports include the following: the complicated sensitivity of batteries with various energy store systems to a temperature change [35] and the uncertainty of energy demand for heating and cooling at low speeds [36]. Some potential influential factors that interact with temperature, including energy efficiency during regenerative braking [37], battery cell equalization optimization issue [38] and battery SOC management [39], have not been well addressed.

Based on real-time temperature information collected during various EV trips, the present study aims to reveal how the ambient temperature affects the energy consumption of EVs. Notably, the interactive effects of ambient temperature on vehicle auxiliary loads are explored. The ambient temperature affects battery efficiency directly and may be correlated with the performance of the vehicle auxiliary loads used for heating, ventilation and air conditioning, which indirectly influence battery efficiency.

Moreover, an attempt is made to improve the accuracy of energy consumption estimation based on sparse observations. This technique is important in practical applications of energy consumption estimates. Based on real-world observations of EVs, an energy consumption model is proposed that considers the following factors: (1) the work opposing the rolling resistance, (2) aerodynamic friction losses, (3) energy consumption depending on the grade of the route, (4) auxiliary load consumption and (5) additional energy losses caused by the instability in the power output of the electric motor due to the influence of ambient temperature. We employed both ordinary least squares (OLS) regression and multilevel mixed effects (MME) linear regression for model validation and parameter estimation.

The paper is organized as follows. The next section provides an introduction to the detailed observation data collected in this study regarding the energy consumption of EVs. Then, in the following sections, the proposed energy consumption model, model specification, estimation results and conclusions are successively discussed.

2. Data collection and description

Considering the factors that influence the energy consumption of EVs under real-world conditions, GPS trajectory data were collected for approximately 500 EVs in Japan from February 2011 to January 2013. The detailed datasets were introduced in our previous papers [16,19]. Thus, herein, we provide only a simple introduction. The on-board equipment for each EV records the following information once per minute: vehicle IDs, vehicle status (operating or charging), instantaneous velocities, SOC, geodesic latitude and longitude coordinates (and the GPS accuracy condition), timestamps, and the operation modes of air conditioning and heating. Although vehicle odometer data were also recorded, these data were not used for our study because the scale of odometer reading is only correct to one kilometre and may introduce more estimation errors. We proposed a model framework to address the challenge of the great difference in the observation particle size and observation errors [16].

Among all of these data, those for 68 EVs in Aichi Prefecture (located in the middle of Japan), collected from February 2012 to January 2013, were selected for use in this paper. Additionally, with the help of map matching technologies and road elevation databases from the Japan Digital Road Map Association, the gradient of each road segment was acquired.

The polling frequency of the GPS reports of EVs was relatively low (once per minute). Therefore, the data cannot provide detailed information regarding actual driving behaviours or the moments at which the SOC changed (which occurred in steps of 0.5% during operation). Thus, we focused on the energy consumption per trip. In total, 39,685 trips after data cleaning [16] were recorded for the 68 EVs. These large-scale data help reduce the possibility of estimation errors due to SOC record errors [14].

To explore the influential factors and determine the trends in energy consumption, various variables were extracted from the trip data. First, the energy efficiency E_i was defined as the average energy consumption per kilometre during trip *i*. The energy consumption was calculated at the kilometre level to assist in understanding the spatial distribution of the energy demand in the study area.

For electricity consumed by the air conditioner and heater, the service times per kilometre were given by the following equations:

$$A_i = \frac{t_i}{d_i} * \frac{a_i}{n_i} \tag{1}$$

$$H_i = \frac{t_i}{d_i} * \frac{h_i}{n_i} \tag{2}$$

where A_i and H_i are the service times of the air conditioner and heater, respectively, during trip *i*; t_i is the travel time; d_i is the travel distance; a_i and h_i are the numbers of GPS points at which the air conditioner and heater, respectively, were switched on; and n_i is the total number of GPS points recorded.

In addition, from the elevation data of the road network in Aichi Prefecture, the gradients of the travel routes were obtained. The percentage of the link length with gradient *j*, denoted by P_j, was used to describe the topographical influence on the energy consumption of the EVs [40]. Based on the meteorological data provided by the Japan Meteorological Agency [41], real-time ambient temperature data, T_i, were also obtained for each trip, and the distribution is illustrated in Fig. 1. The bars show the percent distribution of all trips at each ambient temperature, while the curves show the frequency distribution of trips with different air conditioner and heater usage situations at each ambient temperature. Particularly, the ambient temperature when a trip started was matched to the temperature of that trip. The observed temperature ranged from −5.5 °C to 36.6 °C °C, with 242 trips below 0 °C. The descriptive statistics of the variables are listed in Table 1.

Fig. 2 illustrates the relationship between energy efficiency and ambient temperature. The distribution of the observations exhibits an asymmetrical ‘U’ shape. Three polynomials were tested for fitting the asymmetrical ‘U’ distribution. The third-order polynomial, shown in red, yielded the best fit.

The energy consumption per kilometre at each temperature varied considerably, and trips below 10 °C or above 30 °C exhibited larger variances than trips at other temperatures. Thus, interactive effects associated with complicated temperature factors should be considered, and these effects may arise from the operational environment, cell-to-cell variations, and so on [42].

3. Methodology

3.1. Energy consumption estimation of EVs

As discussed in Section 1, in addition to the auxiliary load conditions, travel distance, and time of day, the ambient temperature may