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Save or Waste: Real Data Based Energy-Efficient Driving

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ABSTRACT Energy consumption is the key to restrict the development of electric vehicles (EV), which is heavily affected by complex driving behaviors. In this paper, we propose a classified driving behavior based energy consumption prediction model, as well as recommended mechanisms for energy-efficient driving. Firstly, utilizing six EVs, we collect real data related to driving behaviors and energy consumption of vehicle in one year. After clustering behaviors of drivers, we present an energy consumption predication model, which accurately forecast the energy consumption caused by different driving behaviors. Motivated by the model, energy-saving strategies are proposed to recommend suitable driving behaviors. The simulation results further indicate that the accuracy of the proposed model is up to 98%. Specifically, the proposed model is less dependence on data volume, which guarantees the precision of more than 96% when the data volume is very small.

INDEX TERMS EVs, real data, driving behaviors, energy consumption.

I. INTRODUCTION

Saving energy is one of the major goals that electric vehicles (EVs) pursue, which has attracted extensive body of research. When Habib *et al.* [1] summarize the current situation of EVs, the charging problem is described in detail. To promote the development of electric vehicle industry, the government and manufacturers keep on launching attractive energy saving schemes [2]. Combined with the forecast shortage of energy, it is of great urgency to propose a reliable model that can accurately predict the energy consumption of EVs.

In the literature, Ahn *et al.* [3] find that highway routes are not always the best choices. However, the decisions of a driver are affected by multiple factors when picking routes [4]. In [5], residential density is proved to have impact on vehicle energy consumption by influencing vehicle mileage and fuel economy. However, only two households at different densities are applied as samples in this research. In 2015 [6], the impact of various environmental factors on the power of electric vehicle batteries is investigated. Based on GPS observation data of 68 EVs, a vehicle energy consumption model is established [7]. Merely considering the climate of Aichi Prefecture, the paper reveals the relationship between ambient temperature and energy consumption. Yang *et al.* [8] only focus on the direct effects of battery degradation. They detect that the degradation of batteries leads to a rise in the energy consumption of EVs. Weather and seasons are hot spots for researchers. Chen *et al.* [9] point out that EVs use the least energy in the summer. Donkers *et al.* [10] suggest drivers pick their routes mainly based on the weather. With the rapid development of driverless technology, the trajectory planning of electric vehicles has been widely studied [11]. Qu *et al.* [12] propose a new vehicle following model based on reinforcement learning, which effectively reduces vehicle energy consumption. In above analyses, more attentions are paid to external factors, while the influence of driving behaviors is relatively ignored.

To address the issue, by establishing a hybrid drivetrain model, Zorrofi *et al.* [13] obtain fuel economy estimates of three driving modes and advise to regulate the driving behaviors of bus drivers. In 2010, the difference in energy consumption caused by moderate driving and aggressive driving is proved to be about 30% [14]. Berry [15]

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recommend aggressive drivers pay attention to reducing acceleration, so that they can achieve maximum energy savings. The differences in vehicle energy consumption under different driving modes are fully demonstrated in the study of Raykin *et al.* [16]. In [17], factors such as temperature, choice of road and driving behaviors are considered. But only one vehicle is used in this work, which makes the data have high correlation. Alvarez *et al.* [18] take data collected by smartphones as characteristic data of driving behaviors. Using a neural network algorithm, they build an estimation model for the battery consumption of EVs. The accuracy of this model is about 95%. Based on instantaneous velocity and acceleration, Zhang and Yao [19] develop an analysis model of vehicle energy consumption, whose accuracy is affected by vehicle speed. When studying the factors that influence the emission of EVs, Rangaraju *et al.* [20] emphasize the importance of taking driving behaviors into consideration. By using a machine learning algorithm, Lee and Wu [21] propose a mileage estimation model. Since energy feedback can change driving behaviors of drivers [22]. Introducing energy feedback is proved to have active impact on reducing energy consumption. Felipe *et al.* [23] estimate the energy consumption of EVs on urban routes. The accuracy of estimation is about 90%. In 2018, by comparing some prominent existing models, the advantages of building vehicle energy consumption models based on driving behaviors are described [24]. The aforementioned models prove that regulating driving behaviors has great potential in energy saving. However, the research on energy consumption models based on driving behaviors is relatively limited. Overall, most of the existing models have the following limitations.

- Most models divide driving behaviors into two or three categories. The classification of driving behaviors can be more detailed.
- For some existing models, the classification criteria of driving behaviors are kind of fuzzy.
- Most models do not point out how the amount of data affects the model performance.
- The accuracy of some existing models depends on the data volume. In terms of these models, the model accuracy is impeded by insufficient types and amount of data.
- The energy recover from regenerative braking is also an important index of EVs. However, there are only a few studies consider both energy consumption and energy recovery.

To improve the above limitations, the collected data are used to build a classified driving behavior based prediction model of energy consumption. By clustering the processed data, we first extract the characteristic data of driving behaviors. Specifically, pedal force, pedal frequency and speed are combined to describe different driving behaviors. Then, using the improved cyclic neural network, the labeled data are trained with the corresponding energy consumption. Based on accurate clustering of drivers, we draw the relation curves between driving behaviors and energy consumption. Next, the simulation is conducted to verify the performance of the proposed model. Results indicate that the accuracy of prediction can reach 98%. Besides, the model can also predict the energy recover from regenerative braking with a high precision. In the end, we put forward recommended mechanisms for each kind of driving behaviors. Contributions of this paper are summarized as follows.

- Classification of drivers. Using data collected from six EVs and one hundred drivers, we extract the characteristic data associated with driving behaviors. The K-means clustering algorithm is used to divide the drivers into four typical groups.
- Prediction model of energy consumption. A classified driving behavior based prediction model of energy consumption is proposed, whose accuracy is up to 98%. In addition, the proposed model is independent on data volume, which guarantees the precision of more than 96% when data are insufficient.
- Prediction of the energy recover from regenerative braking. The proposed model can also predict the energy recovery from regenerative braking with high precision.
- Recommended mechanisms. Motivated by the simulation results, we further offer energy-saving suggestions for each type of drivers. Drivers can achieve lower energy consumption by adjusting their driving behaviors according to the recommended mechanisms.

The following parts are organized as follows. Section II introduces the data base. Then, the data is analyzed in Section III. In the following section, we mainly discuss the classification of drivers. The energy consumption prediction model is proposed in section V. Furthermore, we conduct the simulation and give the recommended mechanisms in section VI. In the end, we conclude the paper.

II. DATA BASE

The overall quality of the energy consumption prediction model depends on the quantity and quality of data base. To this end, for a year, data are collected by six EVs of the same type, so that we can make use of the collected data to establish an accurate prediction model. This section introduces our vehicle data, including experimental background, data collection, types and extraction.

A. EXPERIMENTAL BACKGROUND

The EVs used in this experiment are battery electric buses, whose detailed information is shown in table 1. Especially, all EVs are equipped with computers, sensors and wireless connections. The EVs are all on the market, which obtain ISO9001, ISO/TS16949 quality system standard certification, China compulsory product CCC certification, European Union certification, and get the vehicle export qualification to Europe and the United States. The data collected by such EVs are both reliable and accurate. The time resolution is set by the EV manufacturer to 10 seconds.

Drivers	Location		Time						Data related to driving behaviors					Data related to energy		
	Longitude	Latitude	Year	Month	Date	Hour	Minute	Second	Speed (km/h)	Traction pedal force (%)	Traction pedal frequency	Brake pedal force (%)	Brake pedal frequency	Output energy (kwh)	Recovery energy (kwh)	Mileage (km)
Driver 1	112. 90996	28. 211195	2019	3	18	11	46	40	21	0	0	52	1	16615. 31	7016. 56	15033. 1
	112. 90999	28. 210921	2019	3	18	11	46	50	5	0. 8	1	0	0	16615. 32	7016. 59	15033. 1
Driver 2	113. 00577	28. 195635	2019	3	18	11	46	44	9. 5	0	0	43. 2	1	33986. 59	13393. 55	31813. 1
	113. 00576	28. 195635	2019	3	18	11	46	54	0	0	0	48. 4	1	33986. 59	13393. 56	31813. 1
Driver 3	113. 11712	28. 248713	2019	3	18	11	47	12	24. 5	79. 6	1	0	0	9817. 61	3384. 15	31813. 1
	113. 11718	28. 247785	2019	3	18	11	47	21	48	44. 4	1	0	0	9817. 61	3384. 15	7894. 1

FIGURE 1. Data of three drivers.

TABLE 1. Vehicle information.

Vehicle specifications	Vehicle maker	Model	Model Year	Vehicle Weight	Mode
Length : 8540mm Width : 2470mm Height : 3180mm	CRRC ELECTRIC VEHICLE CO.,LTD.	TEG6851BEV25	2018	12500kg	Pure electric mode

When a vehicle is electrified, the real-time data are automatically uploaded through wireless networks. All data from August 2018 to August 2019 are recorded by the EV management system. The system has such functions as real-time communication, data storage and vehicles monitoring. This data base makes it possible to model relationship between driving behaviors and energy consumption precisely.

The driving behaviors of a driver are affected by some external factors such as temperature, road conditions [25]–[27] and traffic congestion levels [28]. In order to minimize such effects and cover various driving behaviors, we make the following four provisions before the data collection.

Regulation 1. The duration of the experiment is one year.

As one hundred drivers participate in the experiment, the collected data of each driver are insufficient if the experiment lasts too short. In addition, it can be assumed that drivers experience different weather and traffic conditions the same number of times during one year. A long experimental time contributes to reducing the influence of temperature and traffic congestion levels on driving behaviors and ensures the richness of collected driving behaviors.

Regulation 2. The drivers are divided into 17 batches of five to six drivers each. Drivers in the same batch drive at the same time. Different batches of drivers drive at the same time periods on different dates.

Due to the limited number of experimental EVs, the drivers carry out the experiment in batches. Regulation 2 is made to ensure the consistency of the experiment time since the traffic congestion level is proved to influence driving behaviors [28]. For the same batch of drivers, obviously they experience nearly the same temperature and traffic congestion levels. Additionally, the traffic conditions are similar for the same time period of different days. Therefore, the traffic congestion levels experienced by different batches of drivers can be considered similar.

Regulation 3. The road is stipulated. All the drivers are required to drive on the prescribed road.

Although Hamdar *et al.* [25] point out that both weather and road conditions have impact on driving behaviors, they emphasize that the impact of road conditions is significantly greater. In addition, road grade information is proved to affect vehicle energy consumption [26]. Qi *et al.* [27] do excellent work on the relationship between road grade information and vehicle energy consumption. Considering the conclusions of above literatures, the energy consumption is affected by road conditions if the drivers choose their routes at will. By prescribing certain sections of road for experiment, the effect of road conditions is eliminated. More importantly, it ensures that the difference in energy consumption is caused merely by the difference in driving behaviors.

Regulation 4. The mode of the EVs is fixed to pure electric mode. The participated drivers are not allowed to change the vehicle mode.

When a vehicle is in different modes, the accessory load may be different. Different accessory loads result in different vehicle energy consumption [7]. Therefore, we fix the vehicle mode to ensure that the accessory load of each vehicle is basically identical. Thus, the difference in vehicle energy consumption is almost solely due to the difference in driving behaviors.

In a word, the above regulations ensure that the data of each driver can be fully collected. The experiment is consistent in time and space. In addition, microscopic factors such as the accessory load of each EV are guaranteed to be identical by specifying the vehicle mode. Figure 1 shows the data of three drivers in an identical batch. It is clear that they drive in the same road and time, which ensures that drivers experience the similar real-world situations. In addition, it can be seen that the time resolution is indeed 10s.

B. DATA COLLECTION

Overall, the collected data are not only large in quantity, but also abundant in types. The main five types are shown in figure 2. The detailed information about Location can be collected by GPS systems. Location data are used to judge whether the drivers drive in accordance with the experimental regulations. Battery data reflect the general condition of batteries. In addition, they are the bases that remind us to recharge the EVs. We are informed of whether the vehicles are working normally by alarm data. When a vehicle appears abnormal, the corresponding alarm data change immediately. In this way, we can know problems in time to guarantee the security of our experimental. For component data, they are mainly applied to observe the usage of components. At the beginning, the component data of six EVs are basically consistent, so that the number of variables is controlled to the least. As mentioned earlier in the article, there are many kinds of sensors in the EVs. According to the experimental requirements, we can easily obtain relevant sensor data. In fact, besides the types of data shown in figure 2, the systems inside record more details connected with mode selection, communication, help system, version information and mechanical energy.

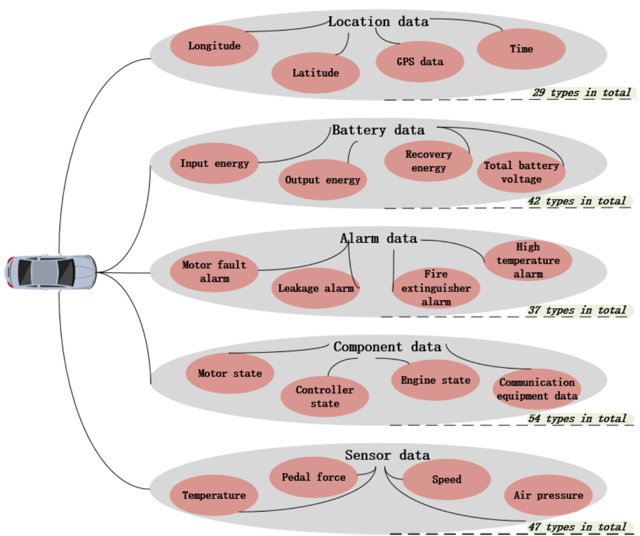

FIGURE 2. Data types.

C. DATA RELATED TO DRIVING BEHAVIORS

When the pedal usages change, it is obvious that the driving behaviors change. Such as light acceleration or heavy braking. Specifically, the pedal usages include the pedal frequency and pedal pressure of both acceleration and brake pedal. The pedal force reflects the aggressiveness of driving behaviors and the pedal frequency is affected by driving proficiency.

Meanwhile, changes in driving behaviors also lead to changes in the vehicle speed and acceleration. However, the real-time acceleration cannot be precisely collected by the EVs. To avoid the increase of error rates caused by recalculation of data, we only choose the primary data that can be directly obtained. Therefore, the five categories of data shown in table 2 are chosen to describe different driving behaviors.

TABLE 2. Data related to driving behaviors.

Symbol	F_a	P_a	F_b	P_b	V
Name	Acceleration pedal frequency	Acceleration pedal pressure	Brake pedal frequency	Brake pedal pressure	Speed

We illustrate the pedal usages of one driver in figure 3 and figure 4.

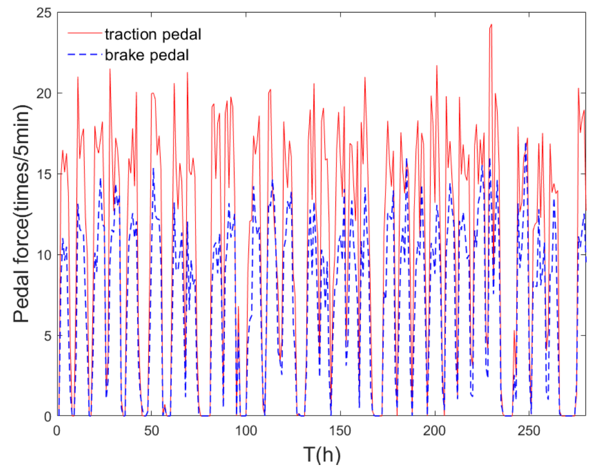

FIGURE 3. Pedal force.

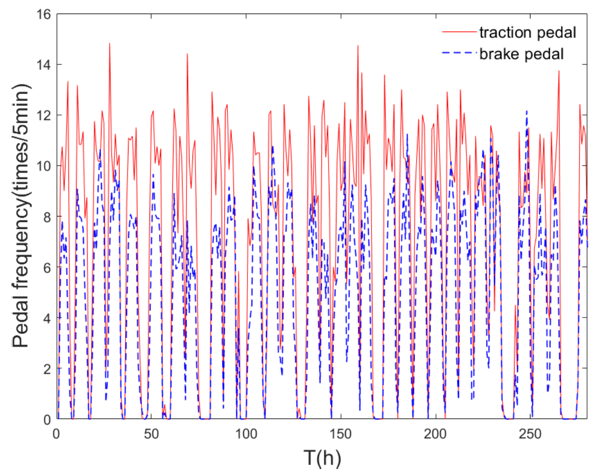

FIGURE 4. Pedal frequency.

D. MEASUREMENT METRICS OF ENERGY CONSUMPTION

The energy consumption of electric vehicles is measured by the change of battery power. In this paper, we consider factors such as the output energy $E_{out}(kwh)$, the energy recover from regenerative braking $E_{recovery}(kwh)$ and the mileage $d(km)$ to define the energy consumption of EVs. The above parameters

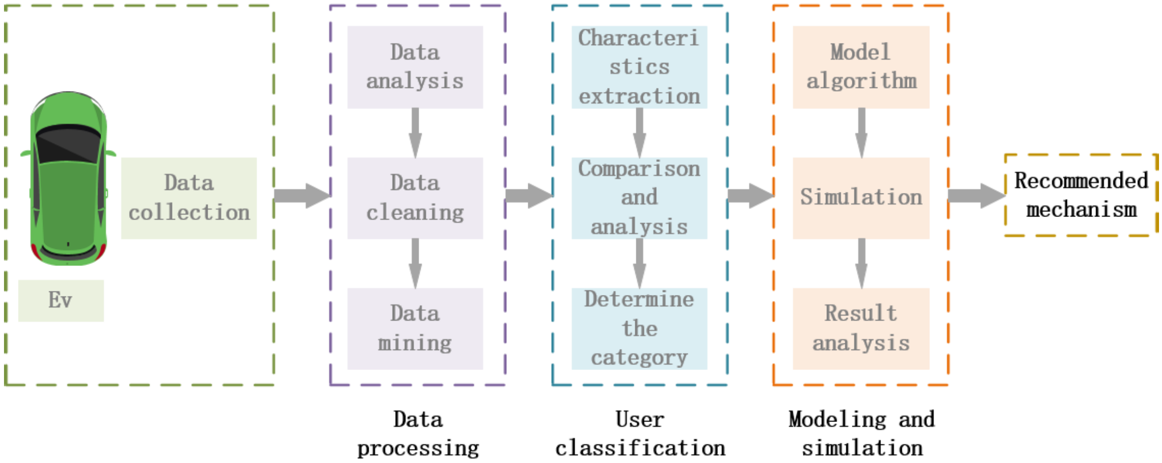

FIGURE 5. Flow diagram of our work.

of three drivers are shown in figure 1. It can be seen that E_{out}, $E_{recovery}$ and d of the three drivers are quite different. The reason is that the recorded mileage and energy consumption are not zero when the driver is changed. Therefore, the actual distance and energy consumption in a time period are the difference between the current value and the initial value.

The types of the energy consumption discussed in this paper include the total energy consumption $E_{total}(kwh)$, the energy consumption at a specified time $E_{time}(kwh)$ and the 100km energy consumption $E_{100km}(kwh/100km)$. The specific definitions are as follows.

$$E_{total} = E_{out} - E_{recovery} \tag{1}$$
$$E_{time} = (E_{O_{end}} - E_{O_{start}}) - (E_{R_{end}} - E_{R_{start}}) \tag{2}$$
$$d_{time} = d_{end} - d_{start} \tag{3}$$
$$E_{100km} = \frac{E_{time} * 100}{d_{time}} \tag{4}$$

where $E_{O_{end}}(kwh)$ and $E_{O_{start}}(kwh)$ represent the output energy at the moment of termination and start respectively. $E_{R_{end}}(kwh)$ and $E_{R_{start}}(kwh)$ represent the recovery energy at the moment of termination and start respectively. d_{end} and d_{start} represent the total mileage at the moment of termination and start respectively.

In addition, the separate output energy and the recovery energy are also important indicators to measure the level of energy saving. In consequence, we also define the output energy at a specified time $E_{O_{time}}(kwh)$, the 100km output energy $E_{O_{100km}}(kwh/100km)$, the recovery energy at a specified time $E_{R_{time}}(kwh)$ and the 100km recovery energy $E_{R_{100km}}(kwh/100km)$ in the following ways.

$$E_{O_{time}} = E_{O_{end}} - E_{O_{start}} \tag{5}$$
$$E_{O_{100km}} = \frac{E_{O_{time}} * 100}{d_{time}} \tag{6}$$
$$E_{R_{time}} = E_{R_{end}} - E_{R_{start}} \tag{7}$$
$$E_{R_{100km}} = \frac{E_{R_{time}} * 100}{d_{time}} \tag{8}$$

The 100km energy consumption is the difference between the 100km output energy. $E_{O_{100km}}$ and the 100km recovery energy $E_{R_{100km}}$.

$$E_{100km} = E_{O_{100km}} - E_{R_{100km}} \tag{9}$$

III. DATA PROCESSING

Figure 5 represents the flow diagram of our work. This section discusses how we process the collected data. The collected data are of great variety. In order to ensure the accuracy and efficiency of our model, we first clean the collected data. According to data analysis, we mainly clean the following three types of data.

- Missing data. Missing data are mostly caused by sensor or communication failure. When data are unsuccessfully collected, the corresponding row is null. Such data are extremely different from normal data. If not cleaned, missing data will cause great negative strikes to the simulation results.
- Irrelevant data. Some data (e.g., ambient temperatures, road conditions, etc.) do not change when a driver changes driving behaviors. That is to say, such types of data are not affected by driving behaviors, which is called irrelevant data. The irrelevant data cannot describe different driving behaviors. Removing the irrelevant features contributes to improve the efficiency of algorithm.
- Unchanged data. Possible heavy traffic congestion or some personal reasons can cause a vehicle remains stationary for a period time. In this case, the data related to driving behaviors and energy consumption are almost unchanged and close to zero. The data collected during this period have no contribution to the analysis of driving behaviors and energy consumption, so it can be cleaned.

For the cleaned data, they are firstly pieced according to the time series. Next, the pieced data are repaired by mean interpolation to avoid waste of correct data. Then, the interpolated data are normalized to reduce the loss function value of the training model and improve the training speed. Furthermore, data mining is carried out to discover suitable types of data associated with driving behaviors. According to the accuracy of sensors and the representativeness of data, we define five types of characteristic data to describe driving behaviors in following ways.

Firstly, we divide the specified time T into n equal parts. Then, in turn, We note the traction pedal force $P_{aT_x}, (x = 0, 1, 2, \ldots, n)$, brake pedal force $P_{bT_x}, (x = 0, 1, 2, \ldots, n)$, traction pedal frequency $F_{aT_x}, (x = 0, 1, 2, \ldots, n)$, brake pedal frequency $F_{bT_x}, (x = 0, 1, 2, \ldots, n)$, and speed $V_{T_x}, (x = 0, 1, 2, \ldots, n)$ at time point T_x. Finally, we average the data and get the following five types of data.

- Mean traction pedal force $\overline{P_a}$

$$\overline{P_a} = \frac{1}{T}\sum_{x=1}^{n} P_{aT_x} \tag{10}$$

- Mean brake pedal force $\overline{P_b}$

$$\overline{P_b} = \frac{1}{T}\sum_{x=1}^{n} P_{bT_x} \tag{11}$$

- Mean traction pedal frequency $\overline{F_a}$

$$\overline{F_a} = \frac{1}{T}\sum_{x=1}^{n} F_{aT_x} \tag{12}$$

- Mean brake pedal frequency $\overline{F_b}$

$$\overline{F_b} = \frac{1}{T}\sum_{x=1}^{n} F_{bT_x} \tag{13}$$

- Mean vehicle speed $\overline{V}$

$$\overline{V} = \frac{1}{T}\sum_{x=1}^{n} V_{T_x} \tag{14}$$

Sensors inside the EVs allow us to obtain the above data in an accurate and efficient way. Besides, the above data vary apparently with different driving behaviors, which well reflect the driving habits of different drivers. Among them, the first four types are intuitive descriptions of driving behaviors, while the fifth type expresses the macro driving habits of a driver. Based on the data, we can make clear classification of drivers.

IV. DRIVER CLASSIFICATION

In chapter 3, five types of characteristic data are defined to describe driving behaviors. In this section, by taking advantage of k-means clustering, participated drivers are partitioned into 4 typical categories. K-means clustering is one of the most commonly used clustering algorithms [29], [30]. In k-means clustering, each observation belongs to the category with the nearest mean. The characteristic data of the four types are shown in figure 6 to figure 9.

Type 1 has the lowest frequencies and high forces on both traction pedal and brake pedal. The traction and brake pedal force of type 1 are close. The two pedal forces of type 2 are nearly the same as that of type 4. Their intensity of pedaling is low, especially braking. Besides, the pedal

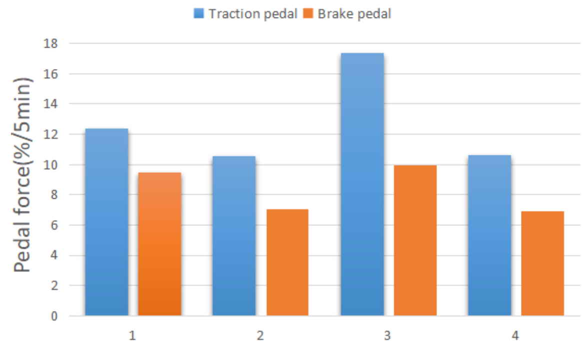

FIGURE 6. Mean pedal force of four types.

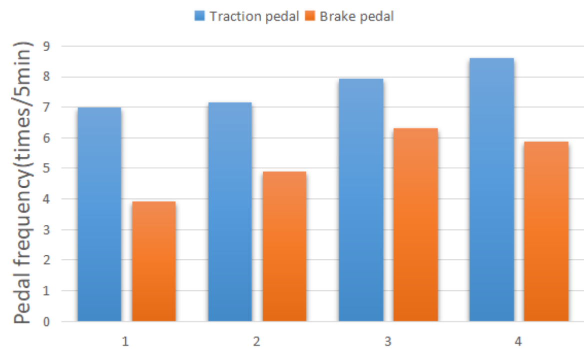

FIGURE 7. Mean pedal frequency of four types.

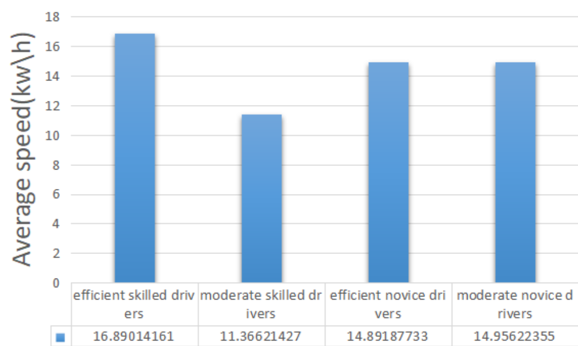

FIGURE 8. Mean speed of four types.

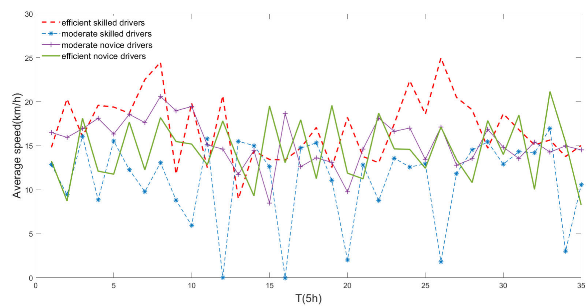

FIGURE 9. Speed of four types.

frequencies of type 2 are relatively low, but they use the brake more frequently than type 1. Type 3 has the maximum pedal forces and braking frequency, whose acceleration force is extremely high. Their acceleration frequency is the second highest. Additionally, the two pedal frequencies of type 3 are the closest. Overall, type 4 has the lowest pedal forces and the highest pedal frequencies. Although their pedal strengths are basically identical with that of type 2, their pedal frequencies are obviously higher than type 2.

It is apparent that the pedal force reflects the aggressiveness and caution of a driver. Moderate drivers tend to pedal more slightly, especially on traction pedal. Therefore, according to the pedal force, drivers are divided into efficient drivers and moderate drivers. Pedal frequency is the embodiment of a driver's proficiency. Novice drivers are less familiar with road conditions and their predictive ability is poor. As a result, they pedal more frequently than skilled drivers, especially the brake pedal. Accordingly, we distribute drivers into novice drivers and skilled drivers. To summarize, combining pedal frequency and pedal force, the four categories of drivers are named as follows.

- Efficient skilled driver (type 1). Such drivers are experienced drivers with great forecasting ability. When speed needs to be changed, they tend to press the pedals hard in advance, rather than frequently accelerating and braking.
- Moderate skilled driver (type 2). Such drivers drive skillfully as well as carefully. They are not accustomed to stepping on the pedals continually or with high intensity. Instead, they prefer pedal ahead of time slightly to alter speed.
- Efficient novice driver (type 3). Although the driving proficiency of such drivers is not that high, they achieve high pedal efficiency by increasing the force on the pedals. It should be noticed that efficient novice drivers always pedal frequently.
- Moderate novice driver (type 4). Owing to unfamiliar with road conditions, moderate novice drivers pedal continually. In addition, such drivers lack experience, which leads them to drive cautiously. In other words, they dare not to push hard on the pedals, especially the acceleration pedal.

The speeds of the four types are shown in figure 8 and 9. As can be seen in figure 8, the average speed of efficient skilled drivers is the highest, while moderate skilled drivers are more habituated to driving at a slower speed. Though the pedal forces of efficient and moderate novice drivers are rather disparate, the distinction on the average speed is not visible. The average speed of novice drivers is between that of efficient and moderate skilled drivers.

Figure 9 indicates that the speed of novice drivers changes more frequently, which is caused by continual pedaling. Besides, accustomed to pedaling with great force, efficient drivers have a wider range of speeds.

In a word, different kinds of drivers have obvious differences in pedal usage as well as driving speed. To analyze the energy consumption caused by different driving behaviors, the pedal force, pedal frequency and driving speed are all required to be considered.

In addition, we draw the total energy consumption curves of four types. In figure 10, the diversity of total energy consumption caused by different driving behaviors is proved to be about 11kwh/h. Comparing the four curves, the curve of moderate skilled drivers shows a stable rising trend over time with smallest changes. However, the curve of moderate novice drivers rises steeply. They consume the most energy. The energy consumption of efficient drivers are similar. Skilled ones consume slightly less energy than novices.

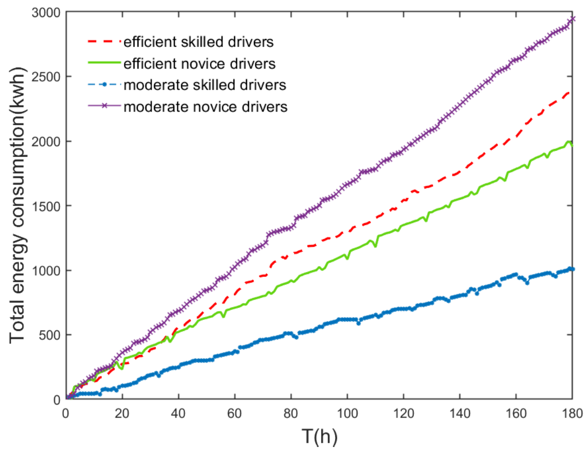

FIGURE 10. Total energy consumption of four types.

V. THE PROPOSED ENERGY CONSUMPTION PREDICTION MODEL

From above analysis, energy consumption is closely related to driving behaviors. In this section, we explore the internal relationship between driving behaviors and energy consumption by establishing a prediction model. Our goal is to build a model that can automatically forecast the energy consumption of any user when the characteristic data of driving behaviors are entered.

Neural networks are well-suited to training large amount of data sets with a high degree of accuracy [31]. Meanwhile, they reduce the processing time drastically compared to other algorithms. Hence, part of the algorithm of our model adopts LSTM (Long Short Term Memory) neural network algorithm [32], which is shown in figure 11. LSTM is a special kind of Recurrent Neural network (RNN) with more complicated internal structure. It not only has the function of long-term memory, but also solves the vanishing gradient and exploding problems in RNN.

For this study, the biggest advantage of LSTM algorithm is that the impact of past data on the prediction is considered. Compared with other NN family algorithms, LSTM algorithm is more adaptable to different situations, which is conducive to improving the universality of the model.

LSTM network consists of three gates, namely input gate, forget gate and output gate. The three gates are used to adjust the transmitted information. The purpose of the LSTM

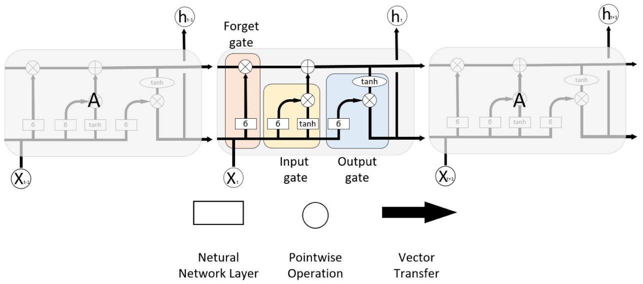

FIGURE 11. LSTM model.

network algorithm is to selectively remember or forget information as well as add new useful information.

The algorithm of our model is shown in figure 12. When data cleaning and data mining are finished, data interpolation is firstly carried out to estimate missing data and constructing new data according to time series. The reason why data interpolation is used here is to avoid the waste of correct data. Then we normalize the data. The goal of data normalization is to change the values to a common scale without distorting the differences of data. The normalized result is denoted as $\overline{X} = \{\overline{P_a}, \overline{P_b}, \overline{F_a}, \overline{F_b}, \overline{V}\}$. In the next step, $\overline{X}$ is imported into LSTM network for model training.

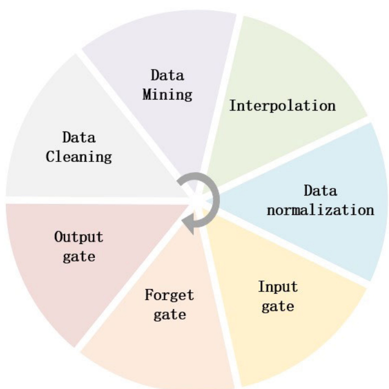

FIGURE 12. Model algorithm.

When predicting energy consumption, $\overline{X}$ first passes through the input gate to discover which data from input should be used to predict energy consumption. Then the forget gate updates the characteristic data of driving behaviors that need to be retrained in the time series. The output gate gives the final prediction results of energy consumption $h_t = \{\overline{E_P}, \overline{E_{OP_{100km}}}, \overline{E_{RP_{100km}}}, \overline{E_{P_{100km}}}\}$. $\overline{E_p}$ is the predicted energy consumption at a specified time. $\overline{E_{OP_{100km}}}$ and $\overline{E_{RP_{100km}}}$ represent the forecast 100km output energy and 100km recovery energy respectively. $\overline{E_{P_{100km}}}$ is the predicted 100km energy consumption.

VI. SIMULATION AND DISCUSSION

Depending on the proposed energy consumption prediction model, we conduct simulation based on collected data in this section. According to the simulation results, the recommended energy saving mechanisms for each type of drivers are given. The effect of data volume on the proposed model is discussed. Additionally, we compare the proposed model with existing well-performed models in terms of model performance and data.

A. SIMULATION

The proposed model adopts the TensorFlow architecture for modeling and simulation based on the Python language.

In consideration of data quantity and simulation accuracy, we choose 70% data for model training and 30% data for model testing. The training data volume is 1000, the time T is 5 minutes. In this way, the influence of bad values is reduced as well as the efficiency and the speed of model training are ensured.

After constant optimization and adjustment, the simulation parameters of our model and their meanings are shown in table 3.

TABLE 3. Simulation parameters and explanations.

Parameter	Value	Explanation
$RunUnit$	12	The number of hidden layer units (obtained by BP neural network).
$InputSize$	5	The input matrix dimension of driving behavior characteristics data.
$OutputSize$	4	The output matrix dimension of energy consumption data.
$LearningRate$	0.0005	The learning rate of LSTM neural network.
$TimeStep$	12	The time step.
$TrainTime$	1000	The times of training.
T	30	The specified time.

The driving speeds of different types are obviously different as shown in figure 8 and figure 9. Therefore, the driving mileage in a specified time of different types are significantly different. That is to say, the energy consumption in a specified time is not only related to driving behaviors, but also affected by driving miles. As a result, the energy consumption in five minutes is not appropriate to compare. The 100km energy consumption is the ratio of total energy consumption to driving mileage. In this way, the 100km energy consumption solves the impact of driving mileage, which is more comparative. Thus, the vehicle energy consumption discussed in the simulation refers to 100km energy consumption.

We firstly analyze the 100km output energy and 100km recovery energy corresponding to different driving behaviors. Figure 13 and 14 respectively show them.

The lower the 100km output energy, the more energy-saving the corresponding type is. In figure 13, efficient skilled drivers appear to be the most energy-efficient, while moderate novice drivers consume far more energy than other drivers. The curve range of moderate skilled drivers is close to that of efficient novice drivers. The 100km output energy of moderate skilled drivers is slightly higher than that of efficient novice drivers.

In figure 14, the type with highest 100km recovery energy is considered to be the optimal one. Accordingly, the efficient

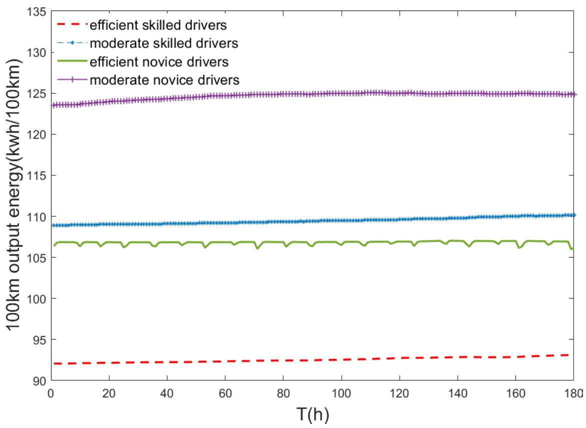

FIGURE 13. **100km output energy of four types.**

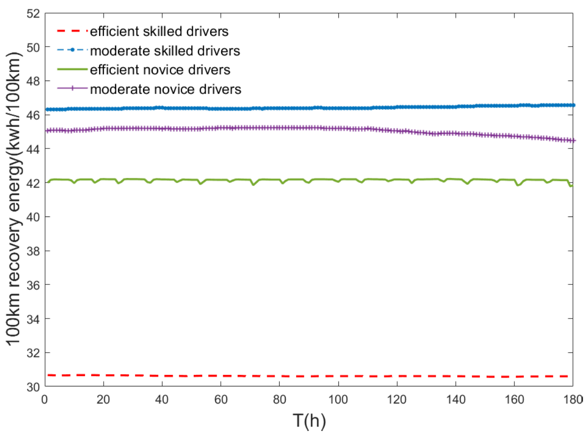

FIGURE 14. **100km recovery energy of four types.**

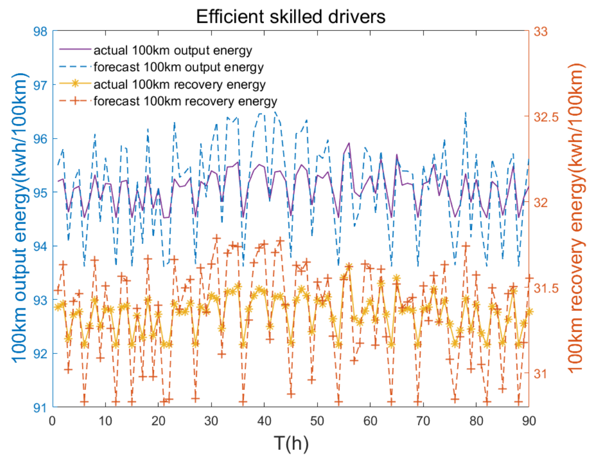

FIGURE 15. **Type 1: Efficient skilled drivers.**

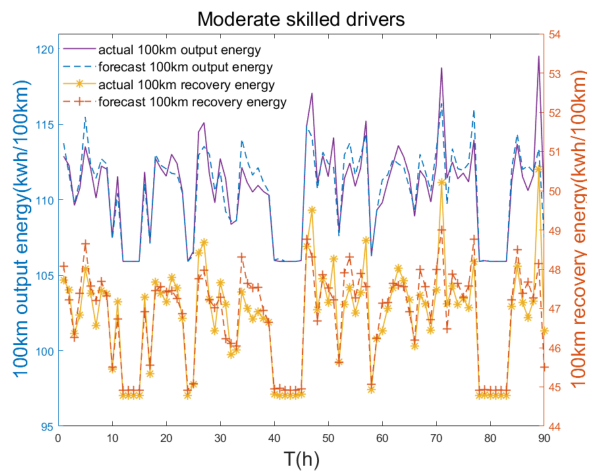

FIGURE 16. **Type 2: Moderate skilled drivers.**

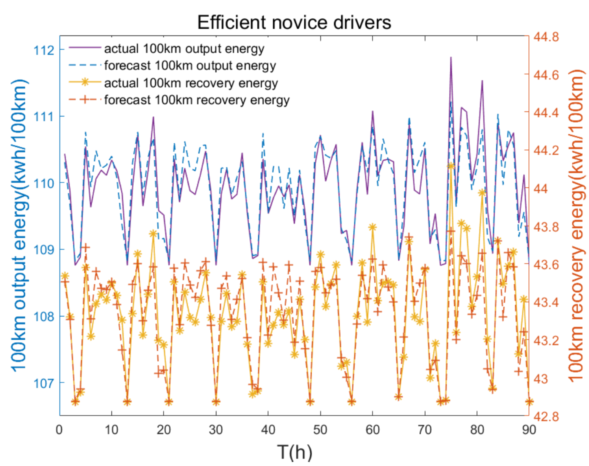

FIGURE 17. **Type 3: Efficient novice drivers.**

skilled drivers become the worst ones while the 100km recovery energy of moderate novice drivers is the second highest. Moderate skilled drivers have the highest braking recovery ability. It is worth noting that the optimal type in figure 13 is inconsistent with that in figure 14.

Combining figure 13 and figure 14, the 100km output energy and 100km recovery energy of efficient skilled drivers are both significantly lower than that of other types. Although the 100km output energy of moderate novice drivers is much higher than that of the other types, their 100km recovery energy is close to that of the moderate skilled drivers and the efficient novice drivers.

The proposed model is able to predict the 100km output energy and 100km braking recovery energy of four types. The results are shown in FIG. 15-18.

As can be seen from the figures, the trends of 100km output energy and 100km recovery energy are almost consistent. This suggests that driving behaviors have similar effects on both 100km output energy and 100km recovery energy. The prediction results are accurate, with the maximum absolute error not exceeding 2kwh/100km. The forecast curves are consistent with the actual curves. That is to say, the proposed model can not only predict the value of energy consumption, but also the trend of energy consumption.

The energy consumption curves of efficient drivers is relatively stable, whose fluctuation range is only about

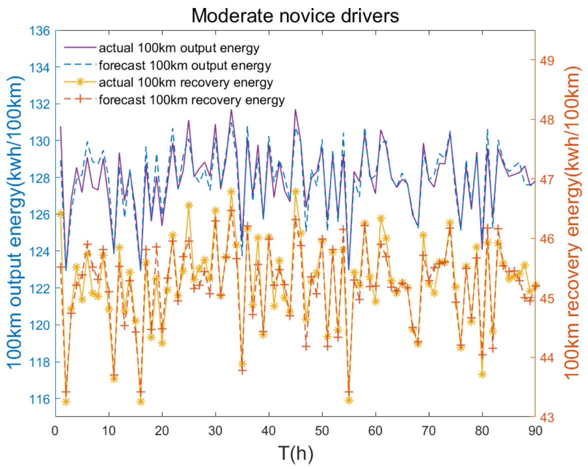

FIGURE 18. **Type 4: Moderate novice drivers.**

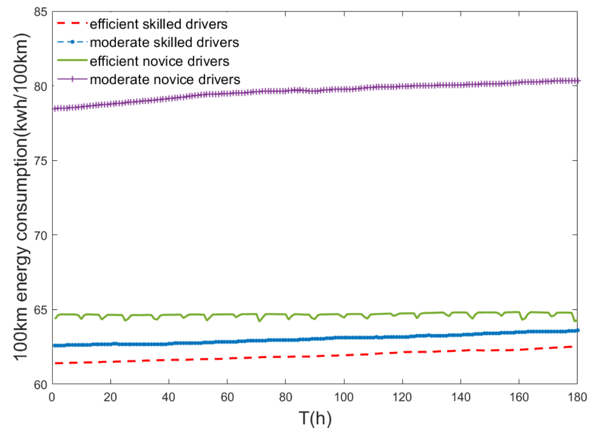

FIGURE 19. **100km energy consumption of four types.**

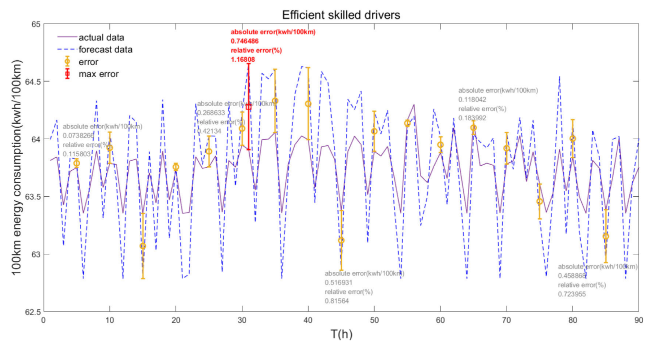

FIGURE 20. **Type 1: Efficient skilled drivers.**

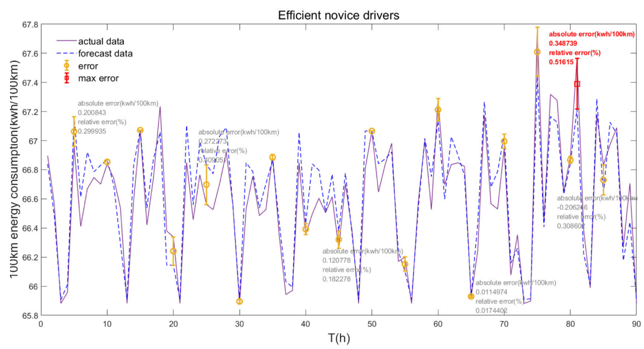

FIGURE 21. **Type 2: Moderate skilled drivers.**

2kwh/100km. While the energy consumption curves of moderate drivers fluctuate greatly, which are up to 10kwh/100km. For drivers with different degrees of driving proficiency, as long as their pedal force is similar, their fluctuation range of energy consumption is close. According to the above analysis, it can be concluded that pedaling with greater force is conducive to more stable energy consumption. Additionally, the influence of pedal frequency on the stability of energy consumption is much less than that of pedal force.

In the analysis of FIG. 13 and FIG. 14, we mention that the relative optimal type reflected by the two figures is different. The above prediction results further prove such inconsistency. It suggests that none of the four types of drivers have the most energy-efficient driving behaviors. Therefore, each type of drivers can achieve lower energy consumption by altering some of their driving habits. The simulation results contribute to indicating how each type of drivers adjust their driving behaviors to achieve further energy saving.

It is not comprehensive to analyze the 100km output energy or 100km recovery energy separately. A comprehensive analysis should combine the two types of energy. 100km energy consumption is defined as the difference between 100km output energy and 100km recovery energy. Since the 100km energy consumption takes into account the above two types of energy, it comprehensively reflects the advantages and disadvantages of different driving behaviors. Therefore, we then analyze and predict the 100km energy consumption corresponding to different driving behaviors. The 100km energy consumption of four types is shown in Fig. 19.

As shown in figure 19, the difference in energy consumption caused by different driving behaviors is up to 20kwh/100km. In figure 19, efficient skilled drivers are relatively energy-efficient ones. This is because their 100km output energy is much lower than that of other three types. However, owing to their terrible energy recovery ability, the gap between the 100km energy consumption of efficient skilled drivers and other types significantly narrows. As for the moderate novice drivers, although their 100km braking recovery energy is high, it is not enough to make up for the waste of 100km output energy. They consume nearly 20% more energy than the other three types. The results also index that the energy consumption of novice drivers is higher than that of skilled drivers. Besides, efficient driving leads to lower vehicle energy consumption.

The 100km energy consumption can also be predicted by the proposed model. Comparing the forecast data with the actual data, we obtain the simulation results shown in figure 20 to figure 23.

As the influence of driving behaviors on the 100km output energy and 100km recovery energy is basically consistent,

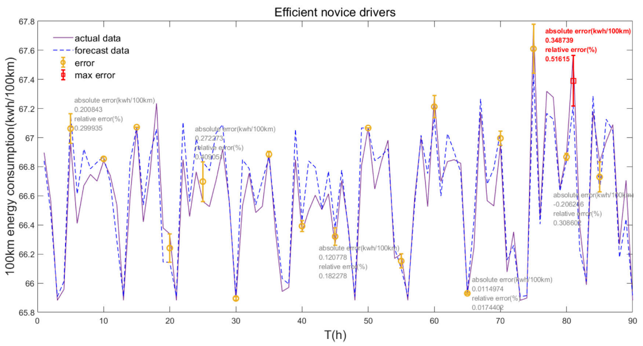

FIGURE 22. Type 3: Efficient novice drivers.

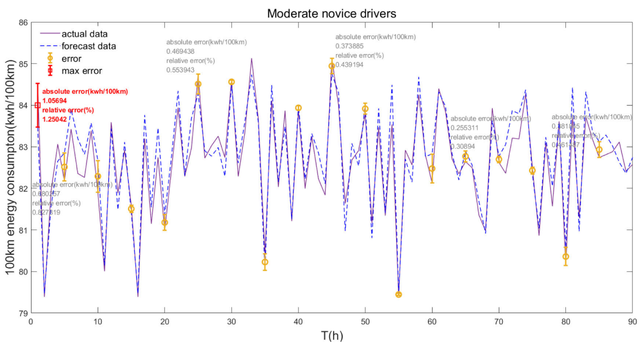

FIGURE 23. Type 4: Moderate novice drivers.

the change trend of 100km energy consumption is also consistent with the two types of energy. For any type of drivers, the variation trends of the forecast results and the actual energy consumption are identical. The absolute error keeps less than 2kwh/100km. In addition, different types have significant distinction in energy consumption. The results further prove the strong correlation between driving behaviors and energy consumption.

Combing with the above analysis of figure 13, 14 and 19, we find that the energy consumption of type 1, type 2 and type 3 are all between 60(kwh/100km) and 70 (kwh/100km). Among them, the average energy consumption of type 1 is the lowest, while that of type 3 is relatively higher. The energy consumption of type 1 and type 3 are both steady, while that of type 2 fluctuates greatly. Type 4 is extremely different from other types, whose energy consumption is much higher than that of the other three types. Moreover, the energy consumption of type 4 changes frequently as well as greatly.

Furthermore, we analyze the differences in energy consumption caused by different driving behaviors. Whether comparing type 1 and type 2, or type 3 and type 4, the results both indicate that greater force is conducive to reducing vehicle energy consumption. Additionally, greater pedal force results in more stable changes in energy consumption, which is already discussed before.

By comparing type 1 and type 4, it can be concluded that brake frequency has an evident effect on energy consumption. The energy consumption of type 4 is much higher than that of type 2, revealing that the increase of acceleration frequency leads to an apparent increase of energy consumption. That's to say, energy consumption drops dramatically by reducing the frequency of any pedal. However, it is worth noting that the decrease of acceleration frequency makes energy consumption more volatile. While the energy consumption is more stable when a driver uses brake less. Yet, among these four types, efficient drivers use both pedals well. This makes it difficult to conclude how the force of the two pedals alone affects energy consumption.

When it comes to type 2 and type 3, we notice that type 2 has better pedaling habits while type 3 uses pedals more efficiently. According to the results, type 2 consumes less energy than type 3. Such results indicate that the influence of frequency is more evident than that of efficiency.

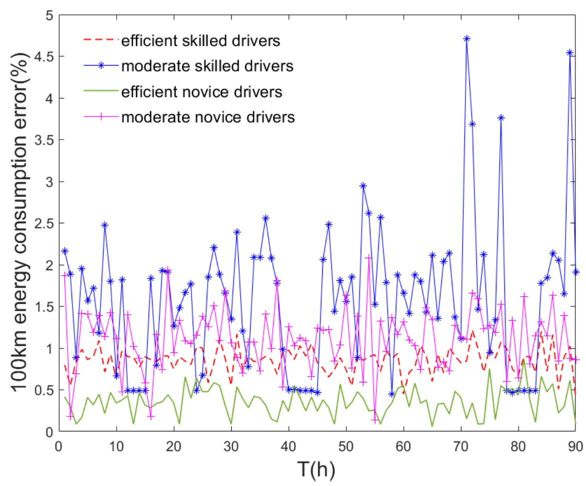

FIGURE 24. Real-time error.

Figure 24 shows the deviation of the proposed model. The maximum real-time error of energy consumption prediction is less than 5%, proving that the real-time prediction accuracy of the proposed model is high. In other words, our model is feasible and practical in predicting energy consumption of drivers with different driving habits. The results have a high reference value for all drivers.

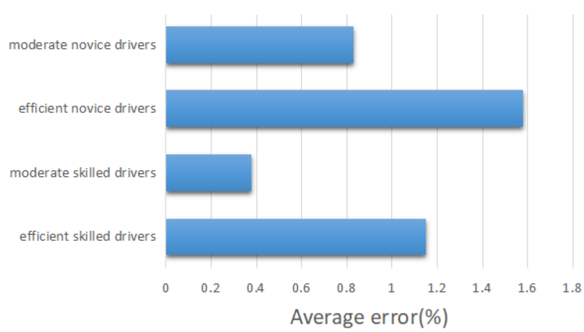

FIGURE 25. Average error.

Figure 25 reveals that the average error of the proposed model is less than 2%, which means that the model precision is more than 98%. In figure 25, we notice that the prediction error of moderate drivers is relatively high. This is because the instantaneous change in energy consumption caused by low-intensity pedaling is relatively small. A small change in energy consumption makes it more difficult to predict precisely. Meanwhile, lower frequency of pedaling increases the error of energy consumption prediction too. Lower frequency means less times of varying, which is not conducive to the prediction of energy consumption.

Moreover, this paper discusses the impact of data volume on the accuracy of model, the results are displayed in figure 26. With the increase in data quantity, the error presents a decreasing tendency. However, regardless of the amount of data, the average error remains stable within 3.5%. That is to say, this model can still maintain great performance when the data volume is thin.

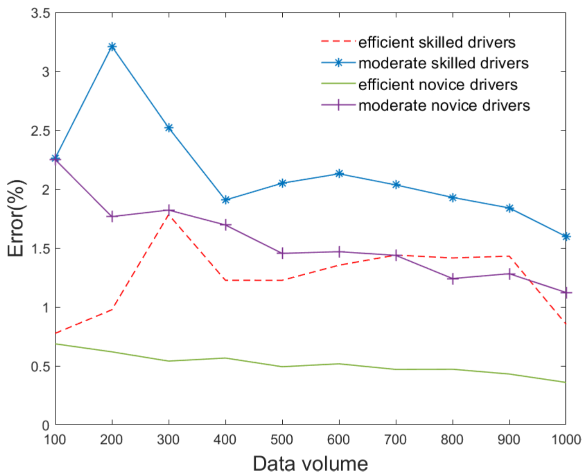

FIGURE 26. Effect of data volume on error.

Combined with the above analysis and FIG. 16, the accuracy of this model keeps higher than 96% when there are only 100 pieces of data. It takes only 100 time intervals to collect 100 pieces of data. The less the interval, the shorter the time required. For the EVs used in this experiment, the time resolution of data acquisition is set to 10 seconds by the EV manufacture. Therefore, it only takes 1000 seconds to collect 100 pieces of data. In consequence, the proposed model has a high real-time performance, which can accurately predict the energy consumption within a short time. What is more, with the increasing of data volume, the prediction error further decreases. According to the predicted results, drivers can adjust their driving behaviors in real time to reduce the energy consumption. After driving for a long time, the prediction accuracy is further improved. At this point, drivers can have a clearer understanding of their driving habits.

Furthermore, we compare the proposed model with some existing models in terms of model performance and data. We mainly choose models with excellent prediction ability. The models are all put forward in recent years. The comparison results are shown in figure 27. Among them, model 1 [18] is based on real data, while model 2 [33] and model 3 [34] are mainly based on theory. In model 1 [18], it is not indicated whether the data volume affects the model performance. However, through reviewing the corresponding paper, we doubt that the data volume might affect the prediction accuracy. In figure 27, the well-behaved parts of each model are highlighted in bold blue.

		Model 1 (2014)	Model 2 (2015)	Model 3 (2018)	The proposed model
Model performance	Model accuracy	95%	95%	95%	**98%**
	Major considerations	Information that can be obtained by phones	Road information	**Changes in driving behaviors**, road information	**Difference in driving behaviors**
	Input variables	Speed, jerk	Speed	Route information	Speed, pedal force, pedal frequency
Data	Whether the model is based on real data	**Yes**	No	No	**Yes**
	Whether validating the model with real data or real situation	**Yes**	**Yes**	**Yes**	**Yes**
	Whether the model accuracy depends on the amount of data	Unclear	—	—	**No**

FIGURE 27. Model comparison.

As can be seen, the accuracy of the existing well-performed models is almost 95%. Thus, the proposed model further improves the prediction accuracy by more than 3%. In addition, more prediction models are based on the theoretical level than modeling with actual data. The research on the relationship between driving behaviors and energy consumption is relatively rare. In this paper, accurate and reliable data are collected during one year. The collected data can not only be used to establish prediction models of EV energy consumption, but also provide a verification basis for some theoretical models. Besides, the proposed model is a prediction model of EV energy consumption based on classified driving behaviors, which to some extent fills the gap of current research. Moreover, although the proposed model is based on real data, the model precision is less affected by the amount of data. The timeliness and universality of the proposed model are appreciable.

B. RECOMMENDED MECHANISMS

Based on the simulation results, we analyze how pedal force and pedal frequency affect energy consumption. Furthermore, we compare the impact degree of pedal frequency and intensity. For pedal frequency, the effects of the two pedals alone are verified. However, through the classified data, it is tough to find out how the acceleration force and braking force affect energy consumption separately.

To solve such a problem, we create type 5 based on the real data. Type 5 is mainly used to compare with type 3 and type 4. In figure 28, their pedal frequencies are close. The main difference between type 3 and type 5 is the acceleration force, while that between type 4 and type 5 is the braking force.

Next, we utilize the proposed model to predict the energy consumption of type 5. The result is shown in figure 29. Compared to type 3, the energy consumption of type 5 decreases slightly. But they achieve much great energy

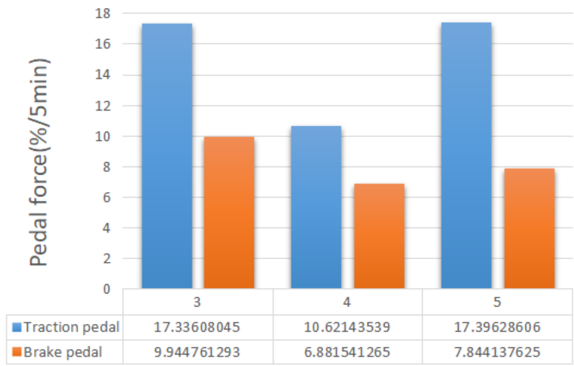

FIGURE 28. Pedal force.

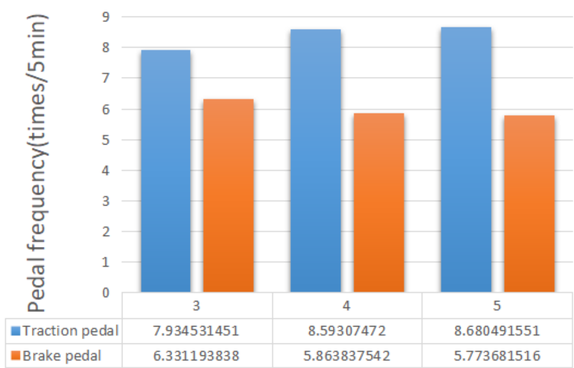

FIGURE 29. Pedal frequency.

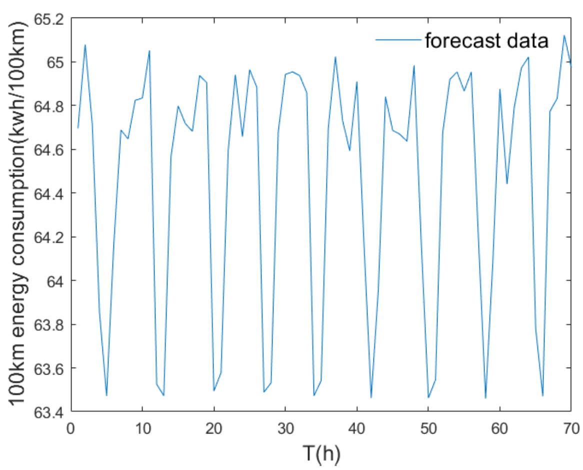

FIGURE 30. 100km energy consumption of type 5.

savings compared with type 4. Besides, the energy consumption of type 5 becomes more stable. This suggests that improving traction pedal strength is much more available for saving energy.

To summarize, the pedal frequency and pedal force both have significant impact on energy consumption of EVs, demonstrating that the characteristic data we select are reasonable to describe driving behaviors. According to the simulation results, pedaling with high intensity and low frequency is considered to be the optimal energy saving scheme. Between the two, frequency has a greater influence on energy consumption than intensity. The energy saving levels of different pedals also differ. The reduction in energy consumption caused by increasing the acceleration pedal force is ten times greater than the reduction by increasing the braking force. Cutting down the frequency of any pedal can significantly lower energy consumption. Specifically, reducing the braking frequency by 24 times per hour can cut down the energy consumption by about 17 (kwh/100km) as well as make energy consumption more stable. Reducing the acceleration frequency by 18 times per hour can cut down the energy consumption by 15 (kwh/100km). But the energy consumption fluctuates more. Finally, we give the corresponding recommended mechanisms for each type of drivers.

- Efficient skilled drivers. Owing the lowest pedal frequency, efficient skilled drivers have the lowest and stable energy consumption among the four types. However, their recovery energy is also the lowest. This is because their acceleration pedal strength is not optimal, with at least 6 percent more room for improvement. That is to say, by increasing the depth of the acceleration pedal, such drivers can further achieve lower energy consumption.
- Moderate skilled drivers. If a user belongs to this category. It means that he is proficient and cautious when driving. However, careful driving leads to the increase in energy consumption. It is what they are required to notice most. As experienced drivers, increasing the pedal strength does not pose a safety problem. In consequence, improving the force of the traction pedal is the most efficient approach for them. Moreover, they can further save energy by reducing the braking frequency.
- Efficient novice drivers. We can say that such users are ‘brave’, because they are not skilled enough but dare to pedal with great force. It is their ’braveness’ that makes their energy consumption not that high. Therefore, as long as they improve their driving proficiency through continual practices, their energy consumption will gradually decrease. Concretely, they ought to practice how to slow down in advance instead of stepping on the brake pedal frequently. This is the most helpful way to them for energy saving.
- Moderate novice drivers. As a matter of fact, most novice drivers are cautious. Unfortunately, such drivers consume too much energy. We can also say that they benefit most from this study. Moderate novice drivers are required to practice more to improve their proficiency. Firstly, we recommend them practice changing speed ahead of time to reduce pedal usage. Then, their driving habits should also be adjusted. Specially, we suggest them increase pedal strength, especially on the acceleration pedal.

VII. CONCLUSION

In this paper, we made use of the real data collected by six electric vehicles to explore the relationship between driving behaviors and energy consumption. We firstly cleaned the data to cluster the drivers. Depending on the driving behaviors, four typical types were classified, including the efficient skilled driver, moderate skilled driver, efficient novice driver and moderate novice driver. Then, we proposed a predication model of energy consumption, which accurately revealed the relationship between driving behaviors and energy consumption. Furthermore, we conducted comprehensive simulation to verify the performance of the proposed model. The results indicated that the accuracy of the model is up to 98%. In particular, the proposed model was less dependent on data volume than most existing prediction models of energy consumption. The model maintained more than 96% accuracy when the amount of data was small. Finally, according to the predication results of the model, we presented suitable recommended energy saving mechanisms for each type of drivers.

Behaviors of one driver were analyzed as a whole in this paper. Relaying on the results we could give suggestions for each kind of drivers. In the future, we will focus on each kind of driving behaviors to analyze the energy consumption and give more detailed recommendations. Additionally, we will take into account microscopic factors such as noise and conduct modeling at the microscopic level.

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