Predictability of Vehicle Fuel Consumption Using LSTM: Findings from Field Experiments

Guanqun Wang[1]; Licheng Zhang[2]; Zhigang Xu, Ph.D., M.ASCE[3]; Runmin Wang[4]; Syeda Mahwish Hina[5]; Tao Wei[6]; Xiaobo Qu, Ph.D.[7]; and Ran Yang[8]

Abstract: It has been well-recognized that driving behaviors significantly impact the fuel consumption of vehicles. To explore how well deep learning methods can predict fuel consumption precisely and efficiently and then guide drivers to go in an energy-saving way, we propose a fuel consumption prediction model, namely FuelNet, based on long short-term memory (LSTM) neural networks in this study. First, we develop the proposed FuelNet model with numerous vehicle kinematics data and corresponding fuel consumption data collected in the test field and real-world scenarios. And we analyze the relationship between the prediction accuracy and different combinations of input variables, training set size, and the sampling interval of the raw data. Second, we conduct intensive field tests to demonstrate the applicability of our model to fuel consumption prediction for different speed conditions and vehicle types. Furthermore, the superior prediction performance of FuelNet is shown by comparing it with five other types of models, such as the physical model, statistical and regression model, conventional neural networks model, and other deep learning models. Finally, we apply it to three real case studies, which verify that FuelNet can precisely predict fuel consumption for different driving trajectories in many scenarios such as signalized intersection (average value of RE is 0.049), campus environments (RE is 0.030), urban roads (RE is 0.077), and highways (RE is 0.097), as well as can contribute to detecting abnormal fuel consumption. **DOI:** 10.1061/JTEPBS.TEENG-7643.

Author keywords: Fuel consumption prediction; Long short-term memory (LSTM) neural networks; FuelNet; Eco-driving; Test site data; Real-world data.

Introduction

The Intergovernmental Panel on Climate Change stated that the world had already warmed by 1°C. This increases the risk of extinction for many species and exacerbates natural disasters and air pollution, posing a serious threat to human health (Kumar 2018; Tollefson 2018). More than 70,000 extra deaths were observed in 12 European countries during the 2003 summer heatwave (D'amato et al. 2016). For every 1°C rise, the risk of premature death was six times higher in respiratory patients than in healthy individuals (D'amato et al. 2016). The World Health Organization (WHO 2021) shows that emissions from the transport sector account for a large and growing share of urban air pollutants, which makes up 30% and 50% of particulate matter emissions in European cities and the Organisation for Economic Co-operation and Development countries, respectively (Rapid Transition Alliance 2020). As a result, many studies have been focused on reducing vehicle emissions. It has been reported that connected and automated vehicles can provide eco-driving strategies for different traffic scenarios (e.g., trajectory optimization for vehicles in intersections and work zones) to reduce fuel consumption (Shladover 2018; Xu et al. 2021). Estimating the fuel consumption of any generated spatiotemporal trajectory is critical for drivers to develop the most energy-efficient driving strategy.

As we all know, an on-board instrument can measure fuel consumption directly. However, if the fuel consumption for any future trajectory of a vehicle can be predicted, the most fuel-efficient trajectory can be sent to the driver or the electronic control unit, which helps the vehicle run in an energy-saving way (Zhang et al. 2020). Fuel consumption prediction is also used to solve a series of intelligent transportation-based issues, such as optimization of intersection traffic, smart lane-changing decisions for an autonomous vehicle, and calculation of remaining mileage.

Traditional Fuel Consumption Models

Recently, many models have been proposed to deal with fuel consumption prediction, including physics-based models, statistical and regression models, and neural network models. The classic physics-based models include the vehicle-specific power (VSP) model (Jiménez-Palacios 1998; Zhang et al. 2022), comprehensive modal emission model (An et al. 1997), EMIssions model (Cappiello et al. 2002), and International Vehicle Emissions model

[1]Ph.D. Candidate, School of Information Engineering, Chang'an Univ., Xi'an 710064, China. ORCID: https://orcid.org/0000-0003-0008-5609. Email: guanqunwang@chd.edu.cn

[2]Senior Engineer, School of Information Engineering, Chang'an Univ., Xi'an 710064, China. ORCID: https://orcid.org/0000-0002-9297-0412. Email: lichengzhang@chd.edu.cn

[3]Professor, School of Information Engineering, Chang'an Univ., Xi'an 710064, China (corresponding author). ORCID: https://orcid.org/0000-0002-8479-4973. Email: xuzhigang@chd.edu.cn

[4]Senior Engineer, School of Information Engineering, Chang'an Univ., Xi'an 710064, China. Email: rmw@chd.edu.cn

[5]Master's Student, School of Information Engineering, Chang'an Univ., Xi'an 710064, China. Email: syeda_hina1@yahoo.com

[6]Engineer, Shaanxi Lingyun Electronics Group Co., Ltd., No. 1 Yuquan Rd., Baoji 721006, China. Email: 425999127@qq.com

[7]Professor, Dept. of Architecture and Civil Engineering, Chalmers Univ. of Technology, Gothenburg SE-412 96, Sweden. ORCID: https://orcid.org/0000-0003-0973-3756. Email: xiaobo@chalmers.se

[8]Master's Student, School of Information Engineering, Chang'an Univ., Xi'an 710064, China. Email: 13643652396@163.com

Note. This manuscript was submitted on August 9, 2022; approved on December 12, 2022; published online on March 13, 2023. Discussion period open until August 13, 2023; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Transportation Engineering, Part A: Systems***, © ASCE, ISSN 2473-2907.

(Guo et al. 2007). Jiménez-Palacios et al. (1998) proposed the vehicle power ratio and established a VSP-based emission model that was applied to fuel consumption and emissions estimation. The comprehensive modal emission model developed by An et al. (1997) can predict exhaust emissions and fuel consumption in real time based on second-by-second real-time engine data. Cappiello et al. (2002) proposed an EMIssions model to estimate instantaneous fuel consumption for light-duty vehicles based on speed, acceleration, and vehicle-specific parameters. Guo et al. (2007) evaluated the International Vehicle Emissions model to estimate emissions from motor vehicles in developing countries. This model requires many inputs that are difficult to collect. Another classic statistical and regression model is the Virginia Tech microscopic (VT-Micro) model established by Rakha et al. (2004). It is used to estimate the fuel consumption and emissions of light-duty vehicles under thermal stability. The model divided the vehicles into different categories according to the vehicle types. Numerous polynomial combinations of speed and acceleration were experimented with to adapt the best coefficient-matching scheme to various vehicle types. They also tested it in a trial-and-error manner against experimental data.

Although these models can obtain reasonable results, most models are based on simulation data and lack correlation with actual road conditions, making the predictions poor. Although a few are based on real data, they cannot cover all road conditions and vehicle type information, making the application scope of the established model narrow. In addition, too many model coefficients and input variables make them difficult to obtain data and computationally inefficient. However, neural network models do not require many input variables, nor do they need to calibrate many model parameters. They only need to establish the correspondence between input and output through network training. Their calculations are neither tedious nor error-prone, and their predictive performance is higher than the other models mentioned above. Furthermore, they can be applied to other road conditions by training the network.

Neural Network Models

Recently, many scholars have used neural network models to predict vehicle fuel consumption. Amer et al. (2014) used an artificial neural network (ANN) with distance, engine size, speed, fuel type, and passengers as inputs to predict the fuel consumption cost. The ANN was also used by Zargarnezhad et al. (2019) to predict vehicle fuel consumption rates for energy distribution companies. They stated that the vehicle fuel consumption rates were highly dependent on the manufacturer, engine displacement, number of cylinders, weight of the vehicle, number of valves, vehicle aerodynamics, tire pressure, and driving conditions. In addition, ANN was used for predicting the fuel consumption of hybrid electric buses (Sun et al. 2021) and trucks in mines (Siami-Irdemoosa and Dindarloo 2015; Soofastaei et al. 2016). Wu and Liu (2011) proposed a predictive system for vehicle fuel consumption using a back-propagation neural network (BPNN). The engine style, vehicle weight, vehicle type, and transmission system type were input parameters for the neural network training and prediction. Furthermore, they used a radial basis function neural network (Wu and Liu 2012) to predict fuel consumption. The prediction results demonstrated that the proposed system was effective. Du et al. (2017) also used BPNN and floating vehicle data to predict fuel consumption. However, its prediction accuracy was lower than the two previously mentioned studies. Yao et al. (2020) used the BPNN, support vector regression, and random forests to predict vehicle fuel consumption based on mobile phone data. The random forest model got the highest prediction accuracy. The generalized regression neural network (GRNN) model was used to predict the energy consumption of an electric vehicle (Masikos et al. 2015) and can predict truck fuel consumption based on data from the Internet of Vehicles (Xu et al. 2018). Li et al. (2022) proposed a multi-view deep neural network to predict the fuel consumption of automobiles with environmental, driver, and vehicle views. Compared to the random forest and gradient boosting decision tree, multi-view deep neural networks performed best. However, the traditional neural network has higher requirements on input features, needs longer training time, and has lower prediction accuracy and generalization performance.

Deep Learning Models

With the rapid development of neural network models, deep learning (Schmidhuber 2015) methods are favored by many scholars because of their strong learning ability, adaptability and portability, and ability to handle high-dimensional and nonlinear relationships. Commonly used deep learning methods include convolutional neural networks (Zhang et al. 2017), recurrent neural networks (RNNs) (Gers 2001; Boden 2002), long short-term memory neural networks (LSTM NNs) (Hochreiter and Schmidhuber 1997), and gated recurrent unit (GRU) (Cho et al. 2014). They have achieved good results in computer vision, speech recognition, and natural language processing. Among these deep neural networks, the RNNs model is popular in time-series prediction. Kanarachos et al. (2019) used RNNs to predict vehicle fuel consumption through processing speed, GPS position, altitude, number of visible satellites, and acceleration data from a smartphone. They performed a parametric analysis to define the suitable RNNs architecture for fuel consumption prediction and obtained a high prediction accuracy. However, RNNs have the vanishing gradient problem (Bengio et al. 1994) in processing long-term dependency information. This problem is that as the gradient conducts, the gradient is dominated by the near-distance gradient, and the far-distance gradient is small. This makes it difficult for the model to learn far-distance information, resulting in low prediction accuracy. Compared with conventional RNNs, LSTM NNs have the key memory cell to capture the features of time series over longer time spans and overcome the vanishing gradient problem. LSTM NNs are considered particularly efficient for long-term time-series prediction (Graves and Schmidhuber 2005; Graves 2014; Greff et al. 2017), such as traffic flow prediction (Altche and De La Fortelle 2017; Yang et al. 2019), machine translation (Sutskever et al. 2014), handwriting generation/recognition (Graves 2014), and pedestrian trajectory prediction (Alahi et al. 2016; Duan et al. 2016). The vehicle fuel consumption data used in this study are time series data with complex nonlinear relationships. Therefore, we chose the LSTM NNs for fuel consumption prediction and conducted extensive field tests, including fuel consumption prediction under different speed conditions, distinct vehicle types, and different driving trajectories, as well as abnormal fuel consumption detection. Thus, when planning the future driving behavior of the vehicle, the driver is provided with the corresponding fuel consumption for different driving behaviors, so that the driver can choose the most energy-efficient one for future driving.

The contributions of this paper are threefold. First, leveraging the development of deep learning techniques, we design an LSTM NNs-based vehicle fuel consumption prediction model, namely FuelNet, and determine its optimal configuration using data collected in the test field and real-world scenarios. FuelNet enables drivers to choose the most energy-efficient driving behavior for future driving by predicting the fuel consumption of future driving trajectories. Second, we compare the fuel consumption prediction performance of FuelNet, VSP, VT-Micro, GRNN, RNNs, and GRU under different speed conditions and find that the proposed FuelNet model is superior to the other five models. The fuel consumption prediction results of the three types of vehicles under different training sets are also compared. Third, FuelNet can be well applied to fuel consumption prediction of different driving trajectories in signalized intersections, campus environments, urban roads, and highways, and can be used to detect abnormal fuel consumption conditions.

The remainder of this paper is organized as follows. First, the vehicle fuel consumption prediction problem is defined, and the total pipeline of FuelNet is introduced. Then the selection process of the optimal configuration of the proposed model is described. Next, three experiments to explore the speed and vehicle type adaptability of FuelNet are shown, and its prediction accuracy is evaluated by comparing it with five recognized models. Then the applications of FuelNet in three use cases are discussed. Finally, several valuable findings of this study are summarized.

Methodology

Problem Statement

The intelligent transportation system can plan many future driving trajectories for the driver. Fig. 1 presents three typical driving trajectories of drivers passing through a signalized intersection scenario. Y_1 represents the trajectory the driver drives at high speed to go through the intersection before the green phase ends. Y_2 represents the trajectory the driver decelerates to stop at the stop line and goes through the intersection in the following green phase. Y_3 represents the trajectory the driver coasts slowly to go through the intersection in the following green phase. These driving trajectories include driving behavior information such as speed, acceleration, and GPS. Based on this information, the fuel consumption corresponding to the driving trajectory can be estimated. In this way, the driver can choose the most energy-efficient driving trajectory for the following driving.

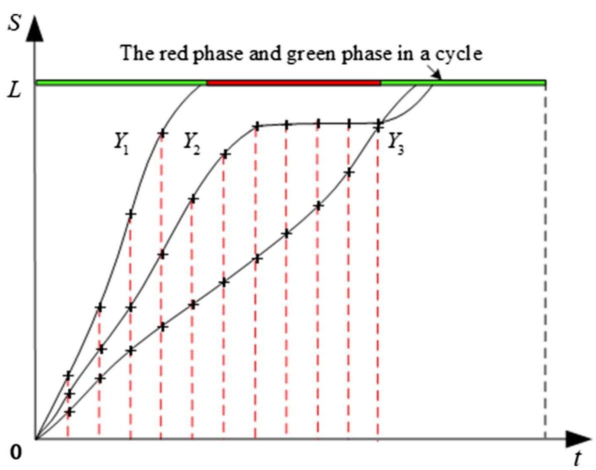

Fig. 1. Traffic flow trajectories.

Fuel consumption and its related data are time series data. There is a nonlinear relationship between fuel consumption and speed, acceleration, GPS coordinates, engine speed, and torque. Therefore, it is necessary to accurately establish the relationship between the instantaneous fuel consumption and other related variables to predict the fuel consumption corresponding to future driving behavior. Fortunately, LSTM NNs is the deep learning network specialized for training and forecasting on time series data. It can solve the vanishing gradient problem faced by other deep learning models when dealing with long-term dependency information, thereby accurately establishing the correspondence between input and output. Therefore, LSTM NNs are used to construct a fuel consumption prediction model in this study.

Structure of the Proposed FuelNet Model

LSTM NNs use the memory cell for storing long-term states (Gers et al. 2000; Altche and De La Fortelle 2017; Yang et al. 2019). It can capture complex correspondences in short- and long-term time series data, thus solving the vanishing gradient problem to a certain extent. This is a significant improvement compared to RNNs.

Fig. 2(a) shows several commonly used LSTM NNs, namely one-to-many, many-to-one, and many-to-many (Graves 2014; Greff et al. 2017). In this study, each input has a corresponding output. This output is final and requires no further conversion. Therefore, we used the LSTM NNs structure of type iii in Fig. 2(a).

To save computation resources and speed up the calculation while ensuring the accuracy of vehicle fuel consumption prediction, a three-layer LSTM NN model was used in this study. It contains an input layer, a hidden layer, and an output layer [see Fig. 2(b)]. The first layer is used to input the historical speed, GPS (longitude, latitude), acceleration, and fuel consumption data. The second layer is used to store the number of nodes in the past states. The output layer is responsible for outputting fuel consumption. In Fig. 2(b), c and h represent the cell state and hidden state, respectively; $\hat{y}$ is the output; [,] means merging the hidden state

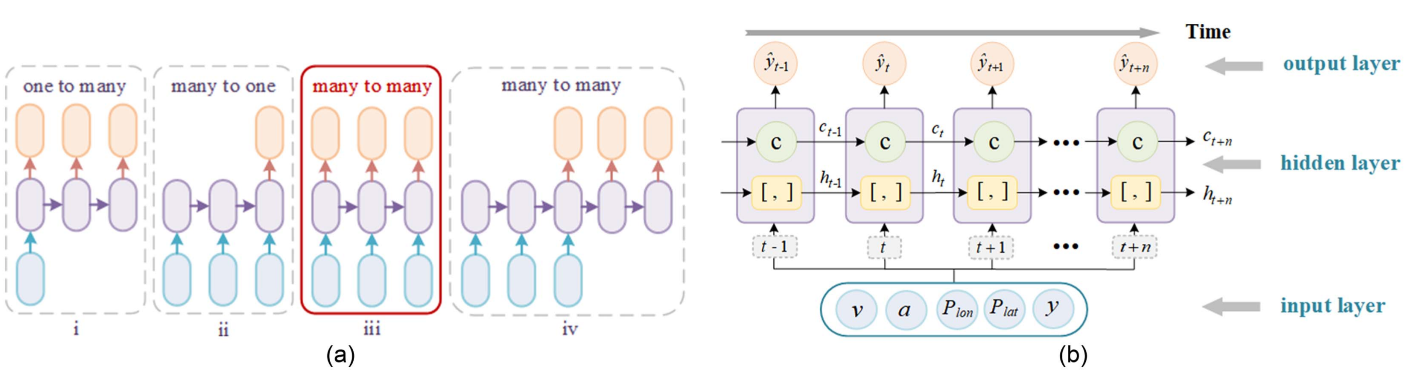

Fig. 2. Structure of FuelNet: (a) commonly used LSTM NNs; and (b) LSTM NNs-based FuelNet model.

at the previous moment with the inputs at the current moment. Descriptions of the inputs and output are listed in Table 1.

The proposed FuelNet model can be formulated by Eq. (1):

$$\hat{y}(t+1) = f_{FCP}(X_{FCP}(t); \Phi) \tag{1}$$

The output variable of FuelNet is $\hat{y}(t+1)$, which denotes the predicted fuel consumption at the next time step $t+1$. $\Phi = \{\phi_1, \phi_2, \ldots, \phi_n\}$ represents the set of parameters of the LSTM NNs. $X_{FCP}(t)$ is the input feature vector at time t, which is generalized as follows:

$$X_{FCP}(t) = \{x_1(t), x_2(t), \ldots, x_m(t)\} \tag{2}$$

where m = number of input features. From Table 1, we can see that m is five, so $X_{FCP}(t)$ can be replaced as follows:

Table 1. Inputs and output of FuelNet

Structure	Variable	Description
Inputs	$v(t)$	Speed
	$a(t)$	Acceleration
	$P_{lon}(t)$	Longitude
	$P_{lat}(t)$	Latitude
	$y(t)$	Fuel consumption at time t
Output	$\hat{y}(t+1)$	Fuel consumption at the next time step

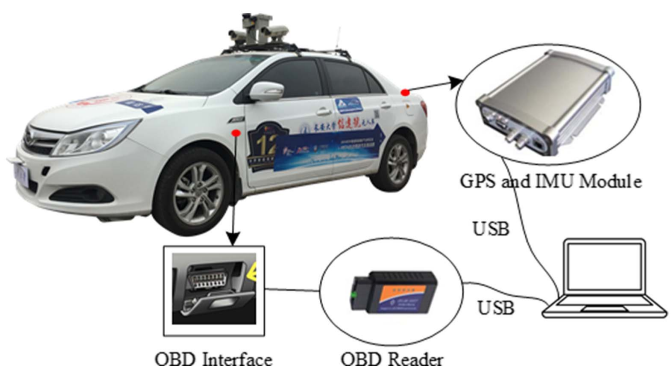

Fig. 3. Data acquisition platform: autonomous vehicle and apparatuses (GPS and OBD). (Images by Guanqun Wang.)

$$X_{FCP}(t) = \{v(t), a(t), P_{lon}(t), P_{lat}(t), y(t)\} \tag{3}$$

The descriptions of $v(t)$, $a(t)$, $P_{lon}(t)$, $P_{lat}(t)$, and $y(t)$ are shown in Table 1.

In this study, we constructed a fuel consumption prediction model based on LSTM NNs, namely FuelNet, and screened out the most suitable variables as inputs. Through comparison experiments, the optimal configuration of the training sequences was determined. Then, based on the field test data, the prediction performance of FuelNet was evaluated under different speeds and vehicle types. Meanwhile, the accuracy and superiority of FuelNet were proved by comparing it with five well-regarded models. Finally, FuelNet was applied to three use cases to verify its excellent prediction performance and applicability.

Optimizing the Configuration of LSTM NNs Based on Field Test Data

Data Acquisition

The autonomous vehicle equipped with GPS and on-board diagnostics (OBD) (see Fig. 3) independently developed by Chang'an University was employed to collect data in the intelligent and connected vehicle test site of Chang'an University (see Fig. 4). As shown in Table 2, the collected data includes the date, time, longitude, latitude, speed, acceleration-x, acceleration-y, acceleration-z, and instantaneous fuel consumption data. The sampling interval of these data is 0.1 s.

Screening of the Inputs

Five fuel consumption-related data were collected: GPS (longitude, latitude), speed, acceleration-x, acceleration-y, and acceleration-z. However, using all of these variables as input features may not achieve the best prediction performance and may even reduce the prediction efficiency. To select the suitable input features for FuelNet, we conducted experiments at speeds ranging from 10 to 80 km/h using five variable combinations as input. We selected 80% of the original dataset for training and the remaining 20% for testing.

Imagery ©2023 CNES / Airbus, Maxar Technologies, Map Data ©2023

Fig. 4. Intelligent and connected vehicle test site of Chang'an University (the closed line is the data collection route). (Imagery © 2023 CNES/Airbus, Maxar Technologies, map data © 2023.)

Table 2. Collected data from OBD

Date	Time	Lon (°N)	Lan (°E)	Speed (km/h)	a-x (m/s^2)	a-y (m/s^2)	a-z (m/s^2)	Fuel consumption (L/100 km)
191,205	80,102.5	108.54129	34.22469	46.25	−0.245	0.01	−1.043	2.21
191,205	80,102.6	108.54129	34.22470	44.4	−0.176	0.031	−1.024	2.21
191,205	80,102.7	108.54130	34.22470	44.4	−0.183	−0.067	−1.053	2.04
191,205	80,102.8	108.54130	34.22470	42.55	−0.224	0.04	−1.006	2.04
191,205	80,102.9	108.54131	34.22470	42.55	−0.25	−0.003	−0.974	2.04
191,205	80,103	108.54131	34.22470	42.55	−0.188	0.023	−0.948	1.92
191,205	80,103.1	108.54131	34.22471	40.7	−0.104	−0.03	−0.992	1.92
191,205	80,103.2	108.54132	34.22471	40.7	−0.148	0.012	−1.011	1.92
191,205	80,103.3	108.54132	34.22471	40.7	−0.228	0.056	−1.069	1.92

The prediction results and errors of FuelNet with five sets of input features are shown in Figs. 5(a–e), respectively.

Fig. 5(a) shows the prediction result and error of FuelNet using speed, acceleration, and GPS as the inputs. Errors are distributed between −0.93 L/100 km and 1.95 L/100 km. 80% of the errors are distributed between −0.5 L/100 km and 0.8 L/100 km. While most errors fluctuate around 0, there are fewer points without error.

In Fig. 5(b), the inputs of FuelNet are GPS and acceleration. Errors are distributed between −0.98 L/100 km and 1.92 L/100 km. 80% are distributed between −0.5 L/100 km and 0.75 L/100 km.

In Fig. 5(c), the inputs are GPS and speed. Errors are distributed between −0.94 L/100 km and 1.93 L/100 km. 80% of the errors are distributed between −0.5 L/100 km and 0.61 L/100 km. The number of points without errors is less than in Fig. 5(b) but more than in Fig. 5(a).

In Fig. 5(d), the input only includes speed. Errors are distributed between −0.95 L/100 km and 0.72 L/100 km. 80% of the errors are distributed between −0.30 L/100 km and 0.35 L/100 km. Compared with Figs. 5(a–c), there are more errors close to 0.

In Fig. 5(e), the inputs are speed and acceleration. Errors are distributed between −0.73 L/100 km and 0.59 L/100 km. 80% of the errors are distributed between −0.29 L/100 km and 0.15 L/100 km, and the overall error is small.

In summary, FuelNet achieves the best performance in fuel consumption prediction when its inputs are speed and acceleration. Conversely, it performs worst when the inputs are speed, acceleration, and GPS. The reason for this is that speed and acceleration are the main manifestations of driving behavior. Both have a significant relationship with fuel consumption (Shui and Szeto 2018). If the input is only speed, the prediction results will be biased in some scenarios. Although the most suitable input features can be determined through the above qualitative analysis, quantitative analysis is still required to verify.

In this study, root mean squared error (RMSE), relative error (RE), and coefficient of determination (R^2) (Alfaseeh et al. 2020; Ma et al. 2017; Qu et al. 2017; Zhang et al. 2021) are used to quantitatively evaluate the prediction results and check the applicability of FuelNet. The definitions are as follows:

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(f_t - \hat{f}_t)^2} \tag{4}$$

$$\mathrm{RE} = \frac{1}{N}\sum_{t=1}^{N}\frac{|f_t - \hat{f}_t|}{f_t} \tag{5}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{t=1}^{N}(f_t - \hat{f}_t)^2}{\sum_{t=1}^{N}(f_t - \bar{f})^2} \tag{6}$$

where $\hat{f}_t$ = predicted fuel consumption; f_t = actual fuel consumption; and $\bar{f}$ = mean of the actual fuel consumption. Smaller RMSE and RE indicate better predictive performance of the model. The value of R^2 ranges from 0 to 1, and the closer the value is to 1, the better the fitting effect.

The RMSE, R^2, and RE of the prediction results of FuelNet under five sets of inputs are listed in Table 3. The best results are marked in bold. It can be seen in Table 3 that the prediction results of FuelNet with different sets of input features under different speed conditions are still satisfactory. All RMSE is between 0.057 and 0.410, and the mean values of R^2 and RE are approximately 0.810 and 0.061, respectively. Therefore, it can be concluded that FuelNet performs well at both low and high speeds.

In addition, the worst prediction performance is obtained when the input features are the GPS and acceleration. Given only speed or speed and acceleration as the input features, the predictions outperform all other input combinations. Furthermore, when the speed exceeds 20 km/h, FuelNet with speed and acceleration as input features has the highest prediction accuracy. However, FuelNet with speed as input achieves the best prediction performance when the speed is less than 20 km/h. This may be because the piezoelectric accelerometer used in this study usually has poor measurement performance when the vehicle on which it is installed is at a low speed (Lu et al. 2018). Therefore, in most cases, speed and acceleration are selected as the input features of FuelNet and converted to speed when the vehicle speed is lower than 20 km/h.

Setting of the Training Size and Sample Interval

To avoid the loss of prediction efficiency caused by the extensive training set size (Samala et al. 2019), we studied the prediction accuracy of FuelNet under different training set sizes (5,000, 10,000, 20,000, 22,500, 25,000, and 30,000). The test set used was the same, of size 1,250. The experimental results are shown in Table 4, indicating that increasing the training set size does not necessarily improve the prediction accuracy. Among the tested candidates, we found that the best-performing training set size was 20,000.

It is important to choose an appropriate batch size for FuelNet to match the training set size (20,000), which directly affects the prediction accuracy and efficiency. To this end, six experiments with different batch sizes (10–500) were performed to obtain the best prediction results, where both the hidden size and the number of iterations were 50. Fig. 6 shows the RMSE for different batch sizes. As per the simulation results, the model has the best performance (RMSE = 0.47) when the batch size is 200. Therefore, the batch size of FuelNet is set to 200.

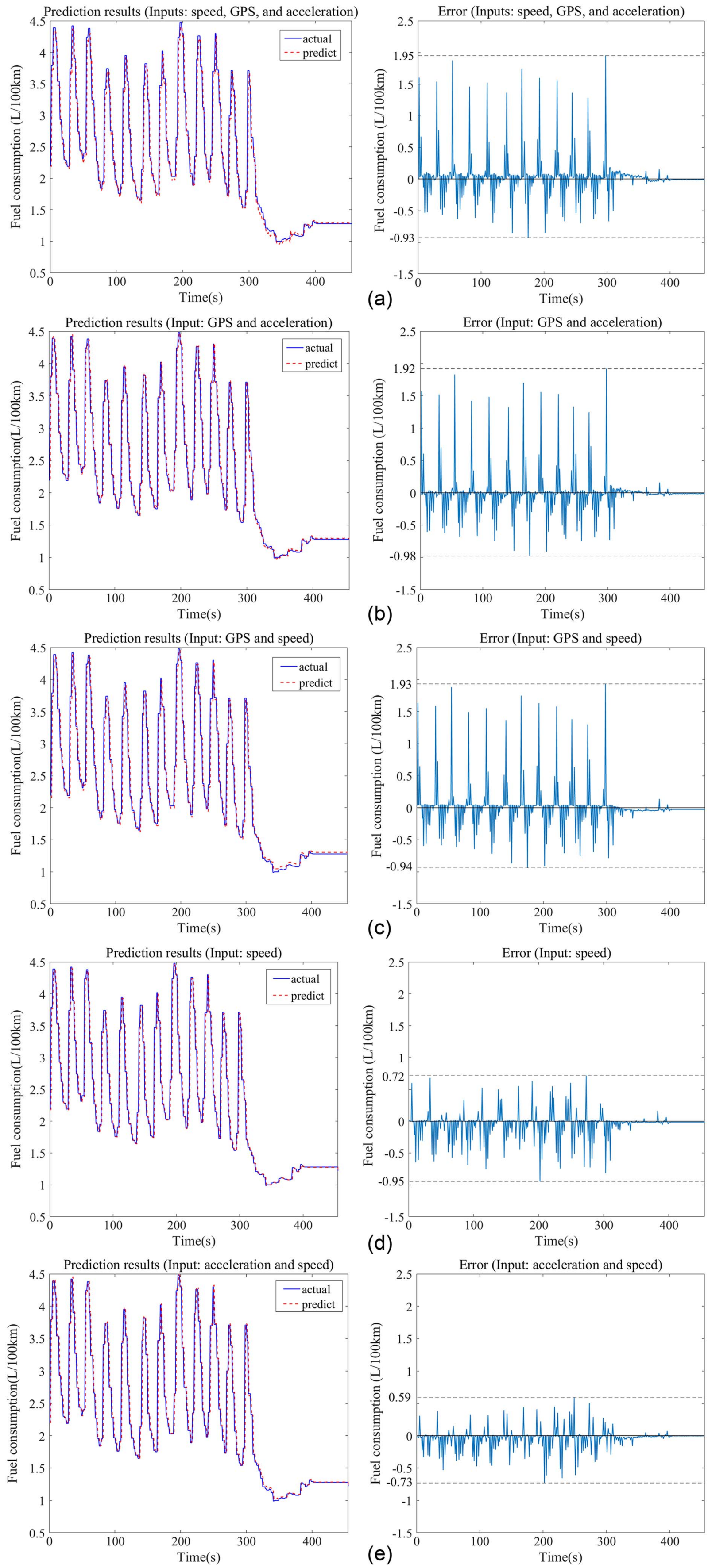

Fig. 5. Prediction results of FuelNet with five sets of inputs (in each subfigure, the left column is the prediction result, and the right is the prediction error): (a) inputs: speed, GPS, and acceleration; (b) input: GPS and acceleration; (c) input: GPS and speed; (d) input: speed; and (e) input: acceleration and speed.

Table 3. Prediction performance of FuelNet with five sets of inputs under different speed conditions

Speed condition (km/h)	Evaluation index	Speed + GPS + acceleration	GPS + acceleration	Speed + GPS	Speed + acceleration	Speed
10	RMSE	0.242	0.173	0.131	0.142	**0.133**
	R^2	0.643	0.666	0.808	0.775	**0.803**
	RE	0.157	0.110	0.070	0.080	**0.072**
20	RMSE	0.170	0.161	0.111	0.059	**0.057**
	R^2	0.614	0.950	0.835	0.954	**0.957**
	RE	0.102	0.019	0.063	0.015	**0.009**
30	RMSE	0.219	0.230	0.247	**0.217**	0.218
	R^2	0.865	0.851	0.828	**0.897**	0.866
	RE	0.049	0.066	0.084	**0.035**	0.035
40	RMSE	0.377	0.370	0.376	**0.360**	0.362
	R^2	0.826	0.832	0.827	**0.829**	0.827
	RE	0.089	0.073	0.059	0.058	**0.056**
50	RMSE	0.328	0.321	0.330	**0.323**	0.326
	R^2	0.891	0.901	0.896	**0.900**	0.899
	RE	0.082	0.051	0.067	**0.043**	0.046
60	RMSE	0.369	0.368	0.368	**0.357**	0.360
	R^2	0.880	0.891	0.891	**0.897**	0.896
	RE	0.057	0.084	0.072	**0.050**	0.053
70	RMSE	0.410	0.399	0.401	**0.387**	0.389
	R^2	0.877	0.879	0.875	**0.878**	0.876
	RE	0.064	0.066	0.071	0.060	**0.058**
80	RMSE	0.361	0.335	0.345	**0.317**	0.320
	R^2	0.978	0.981	0.980	**0.983**	0.983
	RE	0.101	0.042	0.087	**0.029**	0.031

Note: Bold values represent the best prediction results for different speed conditions.

The large size of data often leads to much training time. Therefore, we explored whether downsampling the training data could reduce prediction time while holding performance. The acceleration, speed, and fuel consumption data for eight speed conditions were downsampled using two downsampling rates k (k = total capacity/sample capacity; $k = 2, 4$). It can be seen from Fig. 7 that under eight speed conditions, the RMSE of $k = 4$ is greater than that of $k = 2$; R^2 of $k = 4$ is smaller than that of k = 2, and the RE of $k = 4$ is greater than that of $k = 2$. Moreover, this relationship also exists for the mean values of RMSE, R^2, and RE at $k = 2$ and $k = 4$. Therefore, it can be concluded that the larger sampling interval leads to lower prediction accuracy.

Hyperparameters Tuning

Hyperparameters in LSTM NNs are important and directly affect the prediction accuracy and efficiency. In addition to the batch size covered in the third subsection of the third section, the hidden size, number of iterations, and learning rate need to be carefully tuned. Adam (adaptive moment estimation) was used as the optimization function since it can automatically adjust the learning rate and speed up the convergence. Therefore, only the number of iterations and the hidden size need to be tuned in this study.

A set of experiments was performed to search for the optimal number of iterations between 10 and 500 for FuelNet. In these experiments, the batch size was 200, and the hidden size was 100. Fig. 8 shows that minor differences in RMSE occur on the iterations of 50, 200, and 500. Since a small number of iterations takes less training time, we set the number of iterations to 50.

Next, the hidden size that gives the best prediction performance was explored. The batch size and the number of iterations were set to 200 and 50, respectively. As shown in Fig. 9, the minimum RMSE is reached when the hide size is 200, and the difference in RMSE at hidden sizes of 100 and 200 is minor. However, the large

Table 4. Performance of FuelNet with different training sizes

Training size	RMSE	R^2	RE
5,000	0.338	0.980	0.062
10,000	0.318	0.983	0.040
20,000	**0.314**	**0.983**	**0.028**
22,500	0.316	0.983	0.032
25,000	0.320	0.982	0.041
30,000	0.342	0.980	0.058

Note: Bold values represent the best prediction results.

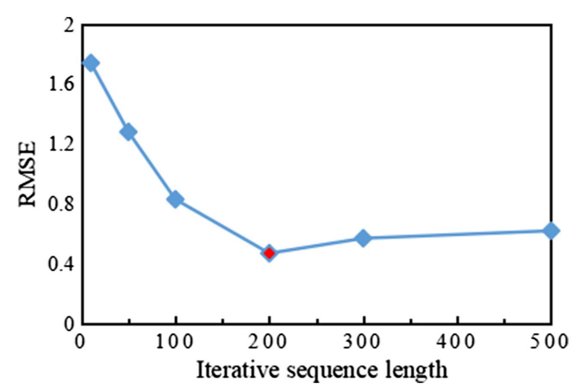

Fig. 6. Variation of the RMSE against different iterative sequence lengths.

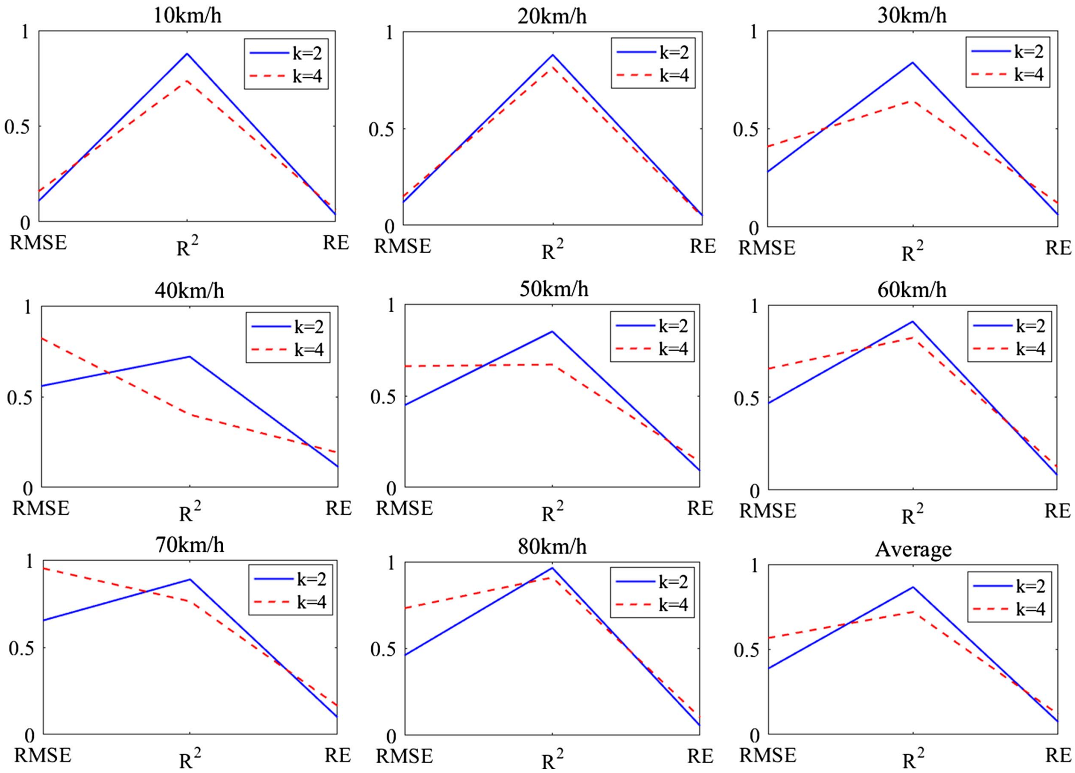

Fig. 7. Comparison of the RMSE, R^2, and RE under $k = 2$ and $k = 4$.

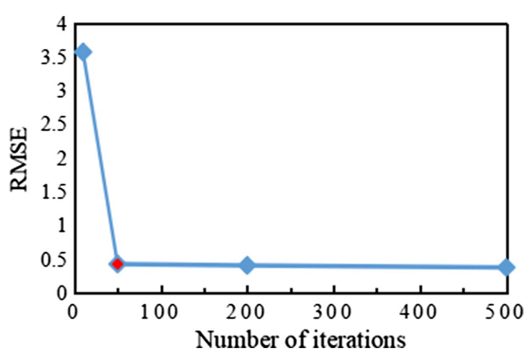

Fig. 8. Variation of the RMSE against different numbers of iterations.

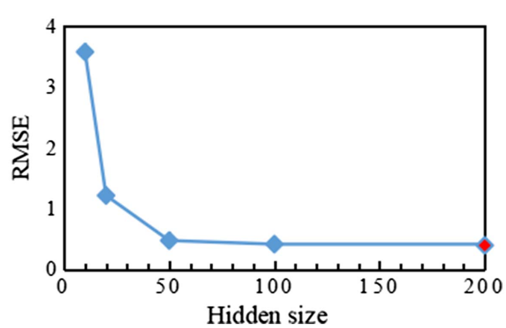

Fig. 9. Variation of the RMSE against different hidden sizes.

hidden size takes more training time. To balance prediction accuracy and efficiency, we set the hidden size to 100.

According to the above experimental results, the batch size, the number of iterations, and the hidden size were set to 200, 50, and 100, respectively. For convenience, the mean absolute error was selected as the loss function. In this study, a computer with a CPU of 3.7 GHz was used for computational experiments using a deep learning framework: Tensorflow1.9.0–CPU + Keras + Spyder3.0.

Field Testing for the Adaptability and Performance of FuelNet and Other Methods

Speed Adaptability Testing

To probe whether FuelNet can accurately predict fuel consumption at different speed conditions (10–80 km/h), eight experiments were conducted using data containing various speed conditions as the training set. As shown in Table 5, FuelNet has good prediction performance under all speed conditions. The mean values of the RMSE, R^2, and RE are 0.274, 0.933, and 0.038, respectively.

Vehicle Types Adaptability Testing

Considering whether the fuel consumption data collected by the host vehicle can be used to predict the fuel consumption of other vehicles, we combined data from a BYD sedan, Honda SUV, and Shaanxi Motor Truck as the training set to predict the fuel consumption of these three vehicles. Partial parameter information about these three vehicles is shown in Table 6. The prediction results are listed in Table 7 (bold indicates the optimal prediction results). It can be seen that using training data from the tested vehicle to predict its fuel consumption yields better results than using mixed training data from different vehicles to predict the fuel consumption of the tested vehicle.

Additionally, we added the vehicle type to the input variables for model training and prediction. The results in Table 7 indicate that using vehicle type, speed, and acceleration as input variables

Table 5. Prediction performance of FuelNet under different speed conditions

Input speed (km/h)	RMSE	R^2	RE
10	0.081	0.932	0.029
20	0.073	0.954	0.014
30	0.201	0.916	0.030
40	0.397	0.858	0.053
50	0.320	0.924	0.048
60	0.335	0.954	0.050
70	0.468	0.942	0.044
80	0.316	0.983	0.035
Average	0.274	0.933	0.038

Table 6. Parameter information of three types of vehicles

Vehicle type	Model	Number of engine cylinders	Displacement	Production date
BYD	QCJ7150WT2	4	1.497L	2014
Honda SUV	HG7205ABC5A	4	1.997L	2016
Shaanxi motor truck	SX4187NL361	6	9.726L	2015

Table 7. Cross-testing between fuel consumption data of three types of vehicles

Input data	Predicted	Added input variable	RMSE	R^2	RE
BYD	BYD	—	**0.454**	**0.944**	**0.063**
BYD + Honda + Truck	BYD	—	0.652	0.852	0.110
		+ vehicle ID	0.704	0.808	0.200
Honda	Honda	—	**0.998**	**0.950**	**0.098**
BYD + Honda + Truck	Honda	—	1.038	0.947	0.098
		+ vehicle ID	1.052	0.907	0.103
Truck	Truck	—	**1.817**	**0.879**	**0.280**
BYD + Honda + Truck	Truck	—	2.250	0.823	0.479
		+ vehicle ID	2.550	0.803	0.542

Note: Bold values represent the best prediction results in each group.

deteriorates the prediction performance. A probable explanation is that the vehicle type variable is a constant, which affects the fit.

Comparison with Other Fuel Consumption Estimation Methods

In this study, the proposed FuelNet model was compared with five well-regarded models (VSP, VT-Micro, GRNN, RNNs, and GRU) at speeds of 10–30 km/h, 30–60 km/h, and 60–90 km/h. The results are shown in Fig. 10. All models performed well in predicting fuel consumption, but FuelNet had the best fit and the lowest error.

Box plots were used to show the relative error results, where the maximum, minimum, median, upper and lower quartiles, and data outliers were displayed. The line in box represents the median. The uppermost and lowermost short black lines represent the maximum and minimum values, respectively. The upper and lower bounds of the box indicate the upper and lower quartiles, respectively. "+" indicates outliers. Outliers are usually regarded as extreme values, which are generally larger or smaller than the whole distribution.

It can be seen that the maximum, minimum, median, upper and lower quartiles, and outliers of the relative errors of FuelNet are the smallest for these three speed conditions. The maximum relative error of FuelNet is around 36%, while that of the other five models is above 50%. In particular, FuelNet achieves the best prediction performance at 60–90 km/h, with most of the relative errors concentrated around 1%. The third column of Fig. 10 shows the absolute error histogram with the abscissa in the range [0, 2 L/100 km] with an internal interval of 0.1 L/100 km. Fig. 10 shows that the absolute error of FuelNet is smaller than other models. The absolute errors of FuelNet are concentrated in [0, 0.1 L/100 km], indicating that the prediction performance of FuelNet is very stable. Therefore, the prediction performance of FuelNet outperforms other models.

As seen from Table 8, the prediction performance of deep learning-based models (FuelNet, RNNs, and GRU) outperforms that of the physics-based model (i.e., VSP) and the statistical and regression model (i.e., VT-Micro). Although there is no significant difference between the RE, RMSE, and R^2 of these three deep learning models, our proposed FuelNet model shows the best performance.

We further compared the prediction performance of different neural network models (FuelNet, RNNs, GRU, and GRNN) with different training set sizes. As shown in Fig. 11, FuelNet has the smallest absolute error of the prediction results among these four models, regardless of the training set size. This result further indicates that FuelNet performs very well in fuel consumption prediction.

Use Cases Testing

Case 1: Fuel Consumption Prediction in a Signalized Intersection Scenario

In Case 1, FuelNet was used to predict the fuel consumption of a vehicle passing through a signalized intersection with different driving behaviors (see Fig. 12) to explore the most energy-efficient driving speeds and accelerations. We planned three kinds of trajectories such as optimal speed, high speed, and stop-and-go; furthermore the test vehicle was driven to follow these planned trajectories (see Fig. 13). We repeated the above experiments three times; simultaneously, the speed, acceleration, and instantaneous fuel consumption of the test vehicle were recorded. The mean speeds of the optimal-speed, high-speed, and stop-and-go trajectories are 31.8 km/h, 68.3 km/h, and 33.9 km/h, respectively. The length of each trajectory is 300 m.

As shown in Fig. 14, for different spatiotemporal trajectories, the predicted values of FuelNet overlap highly with the actual values. A quantitative analysis was performed to analyze the above prediction results more accurately. The RMSE, RE, and R^2 of the results are listed in Table 9, with the best results in bold. The mean values of the RMSE, R^2, and RE are 0.368, 0.901, and 0.049, respectively. The results show that FuelNet performs well in fuel consumption prediction under these three driving conditions. In addition, the optimal-speed trajectory (about 31.8 km/h) is the most fuel-efficient, and the high-speed trajectory (about 68.3 km/h) is the most fuel-consuming. Therefore, when FuelNet is applied to the intelligent transportation system, it can predict the fuel consumption corresponding to the feasible trajectories

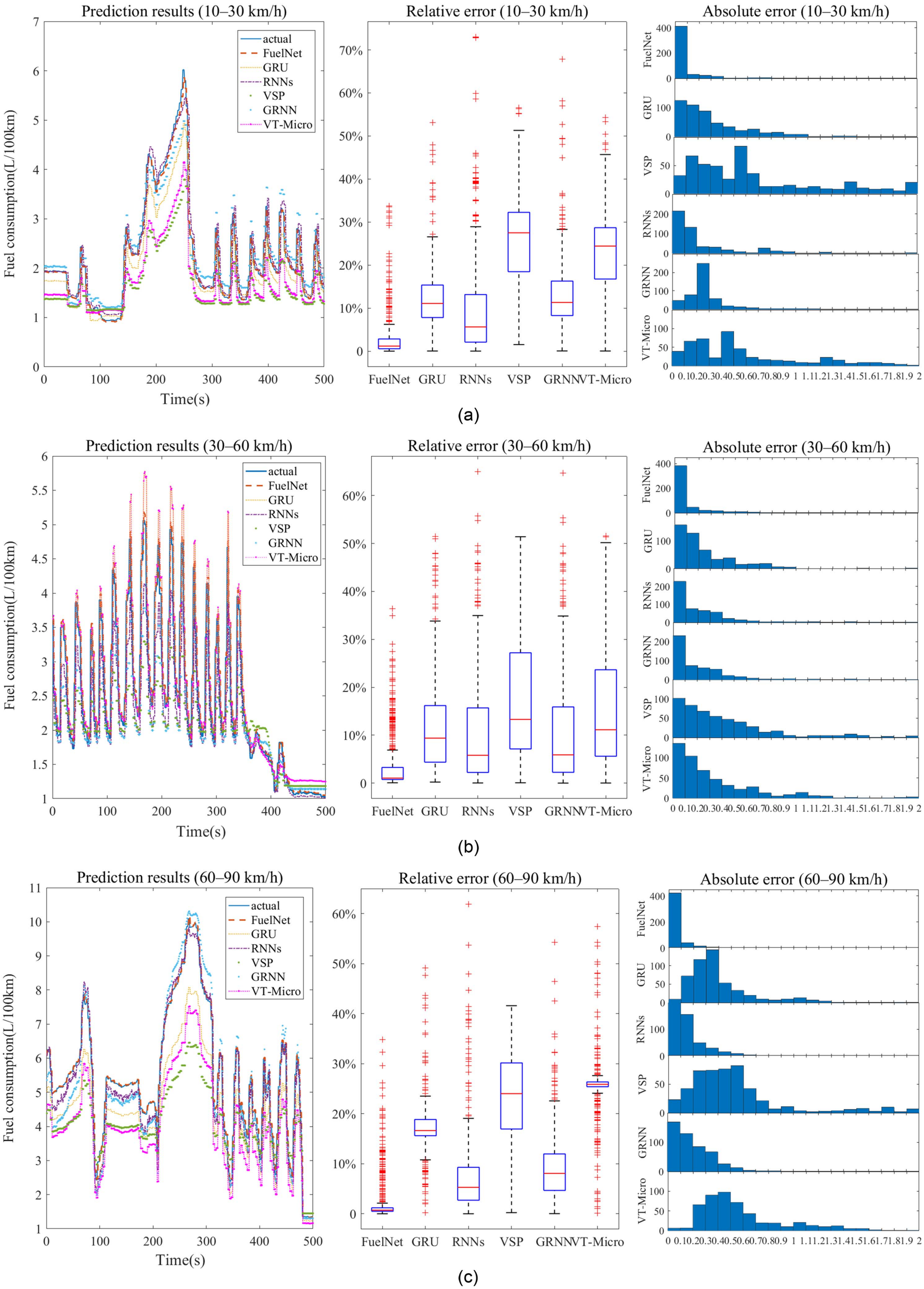

Fig. 10. Prediction results of different models under three speed conditions: (a) 10–30 km/h; (b) 30–60 km/h; and (c) 60–90 km/h.

Table 8. Prediction performance of different models under three speed conditions

Model	10–30 km/h RMSE	10–30 km/h R^2	10–30 km/h RE	30–60 km/h RMSE	30–60 km/h R^2	30–60 km/h RE	60–90 km/h RMSE	60–90 km/h R^2	60–90 km/h RE
FuelNet	**0.135**	**0.936**	**0.021**	**0.394**	**0.978**	**0.055**	**0.376**	**0.975**	**0.038**
VSP	0.907	0.526	0.479	1.351	0.687	0.573	1.300	0.693	0.230
VT-Micro	1.105	0.610	0.409	1.273	0.713	0.623	1.345	0.680	0.256
GRNN	0.353	0.803	0.247	0.832	0.784	0.132	0.711	0.800	0.213
RNNs	0.202	0.909	0.051	0.530	0.961	0.120	0.612	0.934	0.110
GRU	0.558	0.617	0.337	0.821	0.906	0.178	0.982	0.830	0.154

Note: Bold values represent the best prediction results for different speed conditions.

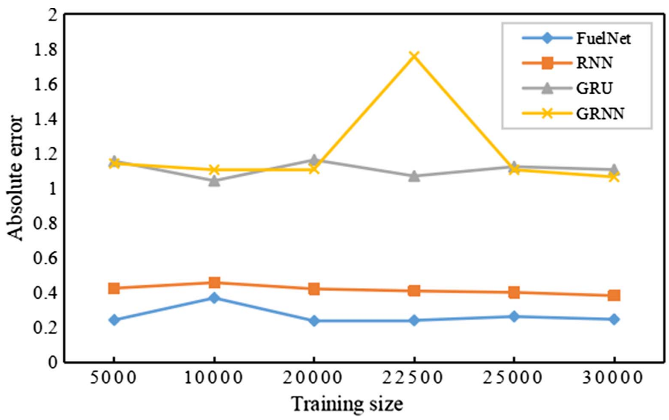

Fig. 11. Prediction results of four models with different training set sizes.

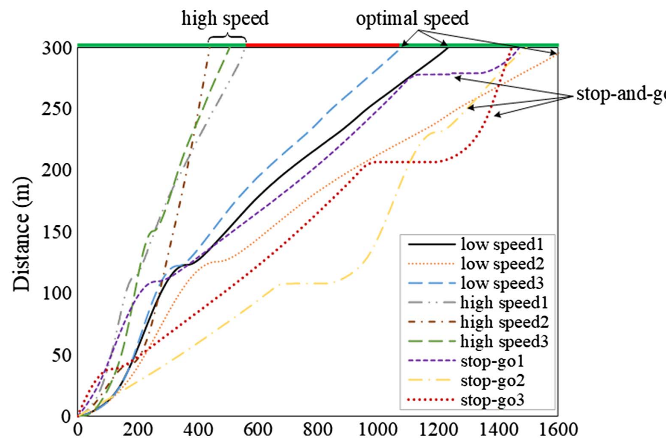

Fig. 13. Driving trajectories for three driving conditions.

recommended by the intelligent transportation system so that the driver can choose the one with the least fuel consumption.

Case 2: Fuel Consumption Prediction in Other Different Scenarios

We further applied fuel consumption prediction to the campus, urban, and highway scenarios. The data we used were collected from Chang'an University, urban roads, and highways in Xi'an. We compared the prediction results of FuelNet, GRU, RNNs, VSP, GRNN, and VT-Micro models under these three different scenarios. As shown in Fig. 15 and Table 10, FuelNet performs the best in each scenario among the six models. The mean values of RMSE, R^2, and RE of FuelNet in these three scenarios are 0.131, 0.996, and 0.068, respectively.

Case 3: Detection of Abnormal Fuel Consumption

In Case 3, FuelNet was used to detect abnormal vehicle fuel consumption. By comparing FuelNet's predicted values with

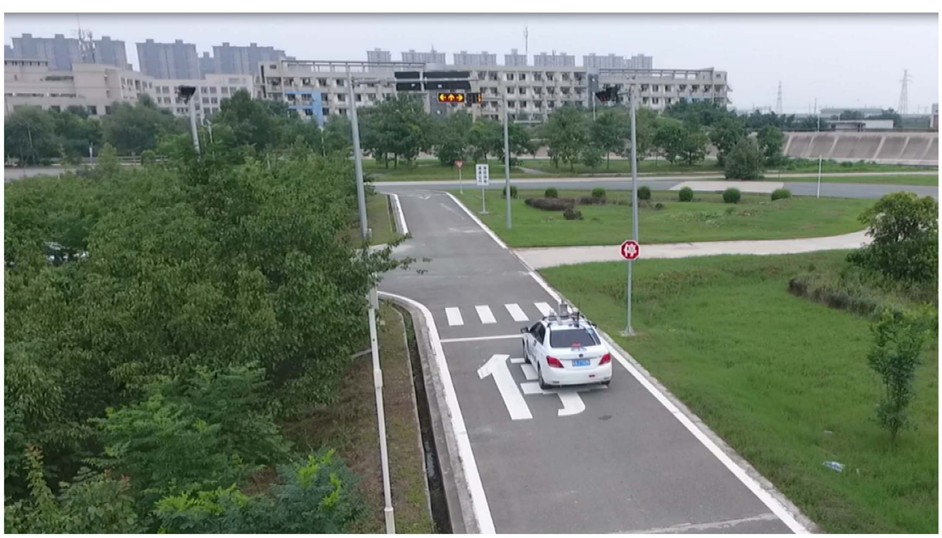

Fig. 12. Signalized intersection test field. (Image by Guanqun Wang.)

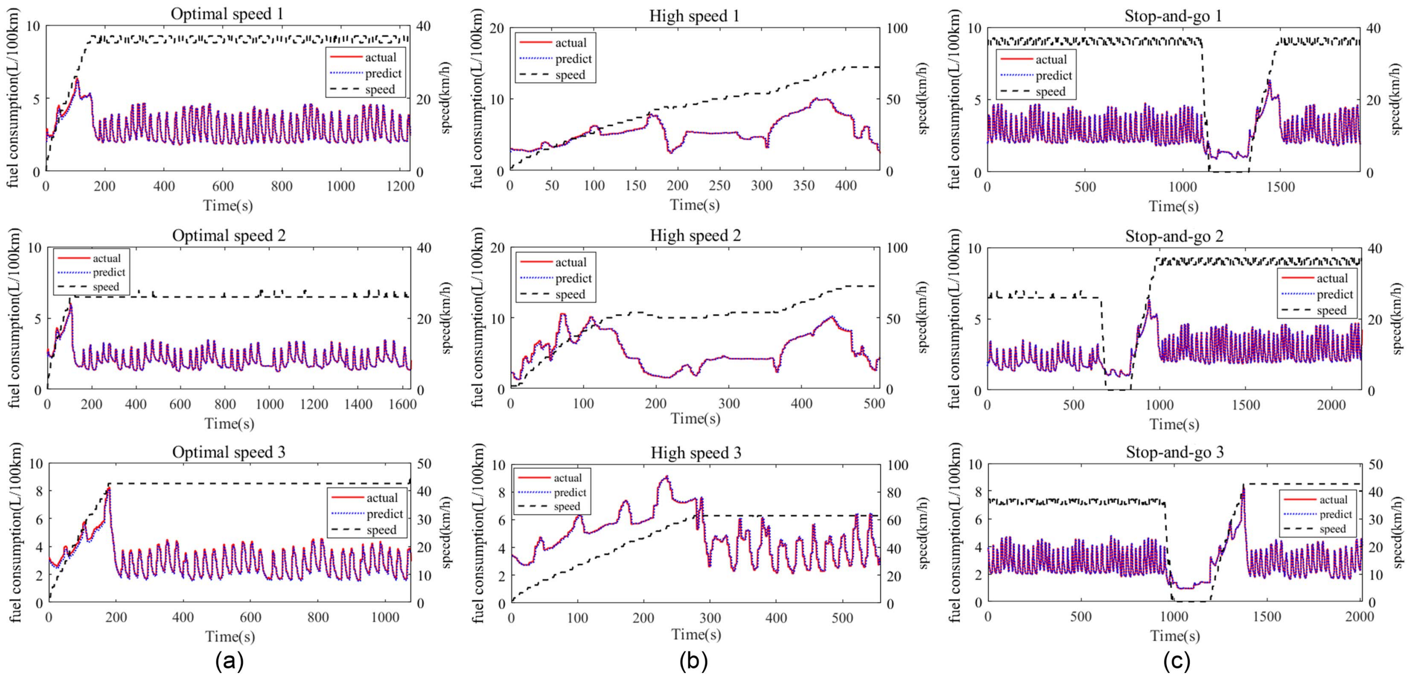

Fig. 14. Prediction results of FuelNet under three driving conditions: (a) optimal speed; (b) high speed; and (c) stop-and-go.

Table 9. Prediction performance of FuelNet under three driving conditions

Driving state	Average speed (km/h)	Predicted fuel consumption (L/100 km)	Actual fuel consumption (L/100 km)	RMSE	R^2	RE
Optimal speed1	33.4	9.08	9.12	0.403	0.844	0.057
Optimal speed2	25.4	6.33	6.32	**0.237**	**0.906**	**0.039**
Optimal speed3	36.6	9.20	9.55	0.334	0.930	0.051
High speed1	70.5	16.48	16.44	0.337	0.982	0.036
High speed2	69.0	14.40	14.31	0.440	0.929	0.053
High speed3	65.5	13.28	13.20	0.439	0.929	0.047
Stop-and-go1	30.7	13.30	13.31	0.403	0.806	0.052
Stop-and-go2	32.1	12.60	12.60	0.377	0.894	0.057
Stop-and-go3	38.9	11.69	11.68	0.345	0.891	0.047
Average				0.368	0.901	0.049

Note: Bold values represent the best prediction results.

actual values, the driver can identify abnormal fuel consumption faults and screen for the cause as early as possible.

The fuel consumption data were collected from a Shaanxi Motor Truck. We performed a dozen data collections and predictions. Here we only present a typical section of the collected data with abnormal fuel consumption (see Fig. 16). It can be seen that the absolute error between the predicted and actual value is small until the 402nd second. After then, the absolute error abruptly increases, reaching a maximum of 7.093 L/100 km. The technician eventually diagnosed that the condition was caused by oil leaking from the pipe connected to the engine.

Conclusions

In this paper, an LSTM NNs-based vehicle fuel consumption prediction method, namely FuelNet, is proposed to guide eco-driving. It can model the long-term dependency characteristics of time-series data by selecting suitable LSTM NNs parameters. Subsequently, the effects of input features, the training set size, and the data sampling interval on the prediction accuracy under different speed conditions are explored. In addition, FuelNet's speed and vehicle type adaptation tests are performed, and FuelNet is compared with five well-regarded models based on the same dataset. Finally, the application of FuelNet for fuel consumption prediction in four different scenarios and abnormal fuel consumption detection proves its practical value.

Several interesting findings are offered in this study:

1. In most conditions, the proposed FuelNet model obtains the best results when the inputs are speed and acceleration. However, in the low vehicle speed cases (≤20 km/h), only the speed is recommended as the input feature for FuelNet.
2. Choosing the raw data with a small sampling interval as the training data can make the prediction result more accurate. Compared with RNNs, GRNN, and GRU, FuelNet has the best prediction performance under different training set sizes.
3. FuelNet can precisely predict fuel consumption in a wide speed range of 10 to 80 km/h, and the results under low-speed conditions are better than those under high-speed conditions.

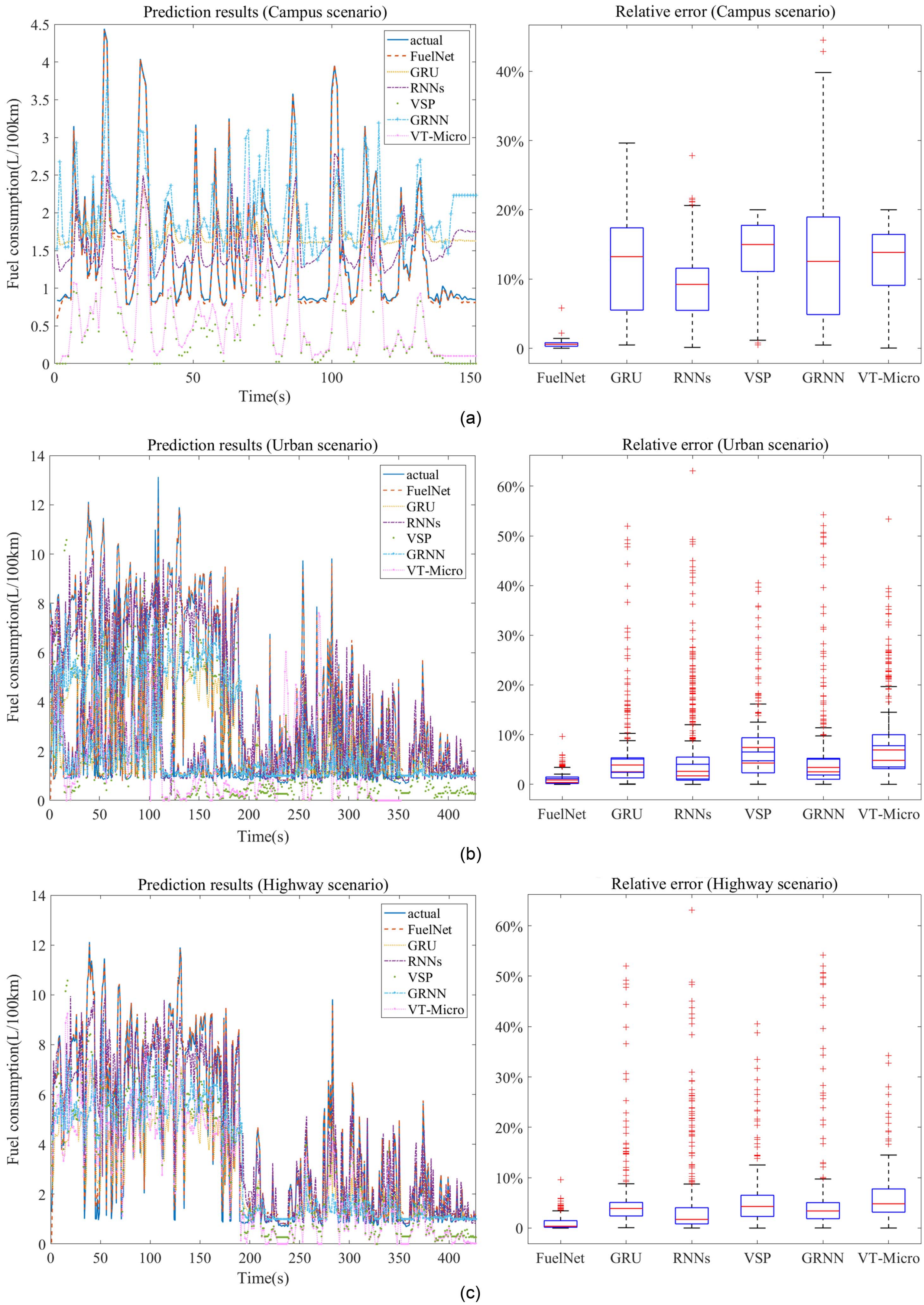

Fig. 15. Prediction results of different models under three different scenarios: (a) campus scenario; (b) urban scenario; and (c) highway scenario.

Table 10. Prediction performance of different models under three different scenarios

Model	Campus			Urban			Highway		
	RMSE	R^2	RE	RMSE	R^2	RE	RMSE	R^2	RE
FuelNet	**0.043**	**0.998**	**0.030**	**0.156**	**0.994**	**0.077**	**0.195**	**0.997**	**0.097**
VSP	1.164	0.126	0.704	2.051	0.210	0.718	1.959	0.647	0.530
VT-Micro	1.0613	0.110	0.651	1.950	0.240	0.898	2.210	0.533	0.580
GRNN	0.624	0.663	0.416	1.677	0.358	0.538	1.709	0.731	0.505
RNNs	0.512	0.771	0.262	1.482	0.498	0.457	1.450	0.806	0.480
GRU	0.811	0.417	0.587	1.945	0.335	0.379	2.427	0.458	0.495

Note: Bold values represent the best prediction results for different scenarios.

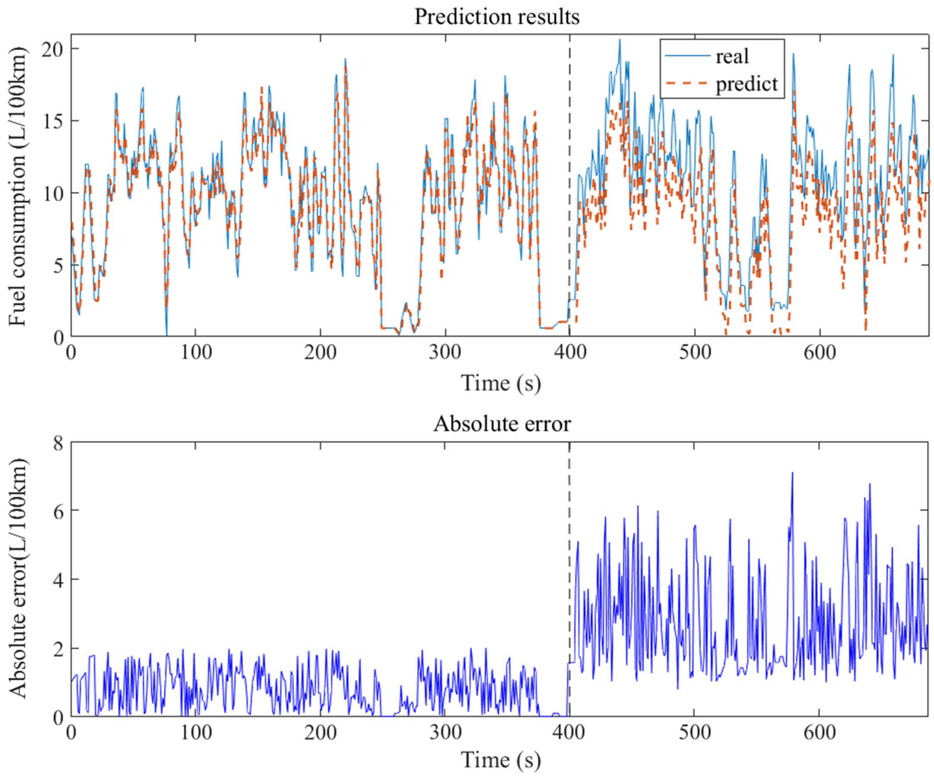

Fig. 16. Prediction results of FuelNet.

4. FuelNet has a superior ability to predict the fuel consumption of distinct vehicle types. Using the host vehicle data as the training set can achieve better results than using the hybrid data from multiple vehicles.
5. A comparison among FuelNet, VSP, VT-Micro, GRNN, RNNs, and GRU shows that the prediction performance of FuelNet is significantly better than that of other models.
6. FuelNet is suitable for fuel consumption prediction of different driving trajectories in many scenarios such as signal intersection, campus environments, urban roads, and highways, as well as for detecting abnormal fuel consumption. It can serve as a reference for drivers to plan their future trajectories for saving energy and reducing emissions.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

This work is supported by the National Key Research and Development Program of China (No. 2019YFB1600100), and the National Natural Science Foundation of China (No. 61973045).

References

Alahi, A., K. Goel, V. Ramanathan, A. Robicquet, L. Fei-Fei, and S. Savarese. 2016. "Social LSTM: Human trajectory prediction in crowded spaces." In *Proc., IEEE Conf. on Computer Vision and Pattern Recognition*, 961–971. New York: IEEE. https://doi.org/10.1109/CVPR.2016.110.

Alfaseeh, L., R. Tu, B. Farooq, and M. Hatzopoulou. 2020. "Greenhouse gas emission prediction on road network using deep sequence learning." *Transp. Res. Part D Transp. Environ.* 88 (Nov): 102593. https://doi.org/10.1016/j.trd.2020.102593.

Altche, F., and A. De La Fortelle. 2017. "An LSTM network for highway trajectory prediction." In *Proc., IEEE 20th Int. Conf. on Intelligent Transportation Systems*, 353–359. New York: IEEE. https://doi.org/10.1109/ITSC.2017.8317913.

Amer, A., A. Abdalla, A. Noraziah, and A. A. C. Fauzi. 2014. "Prediction of vehicle fuel consumption model based on artificial neural network." *Appl. Mech. Mater.* 492 (Jan): 3–6. https://doi.org/10.4028/www.scientific.net/AMM.492.3.

An, F., M. Barth, J. Norbeck, and M. Ross. 1997. "Development of comprehensive modal emissions model: Operating under hot-stabilized conditions." *Transp. Res. Rec.* 1587 (1): 52–62. https://doi.org/10.3141/1587-07.

Bengio, Y., P. Simard, and P. Frasconi. 1994. "Learning long-term dependencies with gradient descent is difficult." *IEEE Trans. Neural Networks* 5 (2): 157–166. https://doi.org/10.1109/72.279181.

Boden, M. 2002. "A guide to recurrent neural networks and backpropagation." *Dallas Project* 2 (2): 1–10.

Cappiello, A., I. Chabini, E. K. Nam, A. Luè, and M. Abou Zeid. 2002. "A statistical model of vehicle emissions and fuel consumption." In *Proc., IEEE 5th Int. Conf. on Information Processing in Sensor Networks*, 801–809. New York: IEEE. https://doi.org/10.1109/ITSC.2002.1041322.

Cho, K., B. van Merriënboer, D. Bahdanau, and Y. Bengio. 2014. "On the properties of neural machine translation: Encoder–decoder approaches." In *Proc., SSST-8, Eighth Workshop on Syntax, Semantics and Structure in Statistical Translation*, 103–111. Doha, Qatar: Association for Computational Linguistics.

D'Amato, G., R. Pawankar, C. Vitale, M. Lanza, A. Molino, A. Stanziola, A. Sanduzzi, A. Vatrella, and M. D'Amato. 2016. "Climate change and air pollution: Effects on respiratory allergy." *Allergy Asthma Immunol. Res.* 8 (5): 391–395. https://doi.org/10.4168/aair.2016.8.5.391.

Du, Y., J. Wu, S. Yang, and L. Zhou. 2017. "Predicting vehicle fuel consumption patterns using floating vehicle data." *J. Environ. Sci.* 59 (Sep): 24–29. https://doi.org/10.1016/j.jes.2017.03.008.

Duan, Y., Y. Lv, and F. Y. Wang. 2016. "Travel time prediction with LSTM neural network." In *Proc., IEEE 19th Int. Conf. on Intelligent Transportation Syst.*, 1053–1058. New York: IEEE. https://doi.org/10.1109/ITSC.2016.7795686.

Gers, F. 2001. "Long short-term memory in recurrent neural networks." Ph.D. Dissertation, École Polytechnique Fédérale De Lausanne.

Gers, F. A., J. Schmidhuber, and F. Cummins. 2000. "Learning to forget: Continual prediction with LSTM." *Neural Comput.* 12 (10): 2451–2471. https://doi.org/10.1162/089976600300015015.

Graves, A. 2014. "Generating sequences with recurrent neural networks." Preprint, submitted August 4, 2013. http://arxiv.org/abs/1308.

Graves, A., and J. Schmidhuber. 2005. "Framewise phoneme classification with bidirectional LSTM and other neural network architectures." *Neural Networks* 18 (5–6): 602–610. https://doi.org/10.1016/j.neunet.2005.06.042.

Greff, K., R. K. Srivastava, J. Koutnik, B. R. Steunebrink, and J. Schmidhuber. 2017. "LSTM: A search space odyssey." *IEEE Trans. Neural Networks Learn. Syst.* 28 (10): 2222–2232. https://doi.org/10.1109/TNNLS.2016.2582924.

Guo, H., Q. Zhang, Y. Shi, and D. Wang. 2007. "Evaluation of the international vehicle emission (IVE) model with on-road remote sensing measurements." *J. Environ. Sci.* 19 (7): 818–826. https://doi.org/10.1016/S1001-0742(07)60137-5.

Hochreiter, S., and J. Schmidhuber. 1997. "Long short-term memory." *Neural Comput.* 9 (8): 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735.

Jiménez Palacios, J. L. 1998. *Understanding and quantifying motor vehicle emissions with vehicle specific power and TILDAS remote sensing*. Cambridge, MA: Massachusetts Institute of Technology.

Kanarachos, S., J. Mathew, and M. E. Fitzpatrick. 2019. "Instantaneous vehicle fuel consumption estimation using smartphones and recurrent neural networks." *Expert Syst. Appl.* 120 (Apr): 436–447. https://doi.org/10.1016/j.eswa.2018.12.006.

Kumar, A. 2018. "Global warming, climate change and greenhouse gas mitigation." In *Biofuels: greenhouse gas mitigation and global warming: Next generation biofuels and role of biotechnology*, 1–16. New Delhi, India: Springer. https://doi.org/10.1007/978-81-322-3763-1_1.

Li, Y., I. Y. Zeng, Z. Niu, J. Shi, Z. Wang, and Z. Guan. 2022. "Predicting vehicle fuel consumption based on multi-view deep neural network." *Neurocomputing* 502 (Sep): 140–147. https://doi.org/10.1016/j.neucom.2022.06.047.

Lu, Y. S., H. W. Wang, and S. H. Liu. 2018. "An integrated accelerometer for dynamic motion systems." *Meas. J. Int. Meas. Confed.* 125 (Sep): 471–475. https://doi.org/10.1016/j.measurement.2018.05.019.

Ma, Z., J. Xie, X. Qi, Y. Xu, and J. Sun. 2017. "Two-dimensional simulation of turning behavior in potential conflict area of mixed-flow intersections." *Comput. Civ. Infrastruct. Eng.* 32 (5): 412–428. https://doi.org/10.1111/mice.12266.

Masikos, M., K. Demestichas, E. Adamopoulou, and M. Theologou. 2015. "Mesoscopic forecasting of vehicular consumption using neural networks." *Soft Comput.* 19 (1): 145–156. https://doi.org/10.1007/s00500-014-1238-4.

Qu, X., J. Zhang, and S. Wang. 2017. "On the stochastic fundamental diagram for freeway traffic: Model development, analytical properties, validation, and extensive applications." *Transp. Res. Part B Methodol.* 104 (Mar): 256–271. https://doi.org/10.1016/j.trb.2017.07.003.

Rakha, H., K. Ahn, and A. Trani. 2004. "Development of VT-micro model for estimating hot stabilized light duty vehicle and truck emissions." *Transp. Res. Part D Transp. Environ.* 9 (1): 49–74. https://doi.org/10.1016/S1361-9209(03)00054-3.

Rapid Transition Alliance. 2020. "Unnecessary travel? The return of breathable air and rethinking transport in a crisis." Accessed June 17, 2022. https://www.rapidtransition.org/stories/unnecessary-travel-the-return-of-breathable-air-and-rethinking-transport-in-a-crisis.

Samala, R. K., H. P. Chan, L. Hadjiiski, M. A. Helvie, C. D. Richter, and K. H. Cha. 2019. "Breast cancer diagnosis in digital breast tomosynthesis: Effects of training sample size on multi-stage transfer learning using deep neural nets." *IEEE Trans. Med. Imaging* 38 (3): 686–696. https://doi.org/10.1109/TMI.2018.2870343.

Schmidhuber, J. 2015. "Deep learning in neural networks: An overview." *Neural Network* 61 (Aug): 85–117. https://doi.org/10.1016/j.neunet.2014.09.003.

Shladover, S. E. 2018. "Connected and automated vehicle systems: Introduction and overview." *J. Intell. Transp. Syst. Technol. Plann. Oper.* 22 (3): 190–200. https://doi.org/10.1080/15472450.2017.1336053.

Shui, C. S., and W. Y. Szeto. 2018. "Dynamic green bike repositioning problem—A hybrid rolling horizon artificial bee colony algorithm approach." *Transp. Res. Part D Transp. Environ.* 60 (Jan): 119–136. https://doi.org/10.1016/j.trd.2017.06.023.

Siami-Irdemoosa, E., and S. R. Dindarloo. 2015. "Prediction of fuel consumption of mining dump trucks: A neural networks approach." *Appl. Energy* 151 (Aug): 77–84. https://doi.org/10.1016/j.apenergy.2015.04.064.

Soofastaei, A., S. M. Aminossadati, M. M. Arefi, and M. S. Kizil. 2016. "Development of a multi-layer perceptron artificial neural network model to determine haul trucks energy consumption." *Int. J. Min. Sci. Technol.* 26 (2): 285–293. https://doi.org/10.1016/j.ijmst.2015.12.015.

Sun, R., Y. Chen, A. Dubey, and P. Pugliese. 2021. "Hybrid electric buses fuel consumption prediction based on real-world driving data." *Transp. Res. Part D Transp. Environ.* 91 (Feb): 102637. https://doi.org/10.1016/j.trd.2020.102637.

Sutskever, I., O. Vinyals, and Q. V. Le. 2014. "Sequence to sequence learning with neural networks." *Adv. Neural Inf. Process. Syst.* 27 (Jun): 3104–3112.

Tollefson, J. 2018. "IPCC says limiting global warming to 1.5°C will require drastic action." *Nature* 562 (7726): 172–173. https://doi.org/10.1038/d41586-018-06876-2.

WHO. 2021. "Urban Health Initiative a model process for catalysing change." Accessed June 17, 2022. https://www.who.int/publications/i/item/WHO-HEP-ECH-AQH-2021.6.

Wu, J. D., and J. C. Liu. 2011. "Development of a predictive system for car fuel consumption using an artificial neural network." *Expert Syst. Appl.* 38 (5): 4967–4971. https://doi.org/10.1016/j.eswa.2010.09.155.

Wu, J. D., and J. C. Liu. 2012. "A forecasting system for car fuel consumption using a radial basis function neural network." *Expert Syst. Appl.* 39 (2): 1883–1888. https://doi.org/10.1016/j.eswa.2011.07.139.

Xu, Z., Y. Wang, G. Wang, X. Li, R. L. Bertini, X. Qu, and X. Zhao. 2021. "Trajectory optimization for a connected automated traffic stream: Comparison between an exact model and fast heuristics." *IEEE Trans. Intell. Transp. Syst.* 22 (5): 2969–2978. https://doi.org/10.1109/TITS.2020.2978382.

Xu, Z., T. Wei, S. Easa, X. Zhao, and X. Qu. 2018. "Modeling relationship between truck fuel consumption and driving behavior using data from internet of vehicles." *Comput. Civ. Infrastruct. Eng.* 33 (3): 209–219. https://doi.org/10.1111/mice.12344.

Yang, B., S. Sun, J. Li, X. Lin, and Y. Tian. 2019. "Traffic flow prediction using LSTM with feature enhancement." *Neurocomputing* 332 (Jan): 320–327. https://doi.org/10.1016/j.neucom.2018.12.016.

Yao, Y., X. Zhao, C. Liu, J. Rong, Y. Zhang, Z. Dong, Y. Su, and F. Chen. 2020. "Vehicle fuel consumption prediction method based on driving behavior data collected from smartphones." *J. Adv. Transp.* 2020 (Mar): 1–11. https://doi.org/10.1155/2020/9263605.

Zargarnezhad, S., R. Dashti, and R. Ahmadi. 2019. "Predicting vehicle fuel consumption in energy distribution companies using ANNs." *Transp. Res. Part D Transp. Environ.* 74 (Sep): 174–188. https://doi.org/10.1016/j.trd.2019.07.020.

Zhang, H., J. Sun, and Y. Tian. 2020. "The impact of socio-demographic characteristics and driving behaviors on fuel efficiency." *Transp. Res. Part D Transp. Environ.* 88 (Aug): 102565. https://doi.org/10.1016/j.trd.2020.102565.

Zhang, K., W. Zuo, Y. Chen, D. Meng, and L. Zhang. 2017. "Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising." *IEEE Trans. Image Process.* 26 (7): 3142–3155. https://doi.org/10.1109/TIP.2017.2662206.

Zhang, L., K. Peng, X. Zhao, and A. J. Khattak. 2021. "New fuel consumption model considering vehicular speed, acceleration, and jerk." *J. Intell. Transp. Syst. Technol. Plann. Oper.* 27 (2): 1–12. https://doi.org/10.1080/15472450.2021.2000406.

Zhang, L., T. Zhang, K. Peng, X. Zhao, and Z. Xu. 2022. "Can autonomous vehicles save fuel? Findings from field experiments." *J. Adv. Transp.* 2022 (Jul). https://doi.org/10.1155/2022/2631692.

J. Transp. Eng., Part A: Systems, 2023, 149(5): 04023030