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RESEARCH ARTICLE

Long-Short Term Memory-Based Heuristic Adaptive Time-Span Strategy for Vehicle Speed Prediction

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ABSTRACT Vehicle speed prediction plays an important role in vehicle energy saving and safety research. It can contribute to vehicle energy saving and safety assistant driving, route navigation, automatic transmission gear control, and hybrid electric vehicle predictive control. The research on vehicle speed prediction has important theoretical basis and application value. The data-driven deep learning (DL) model provides a powerful method for building an accurate speed prediction model. However, the traditional vehicle speed prediction model has some limitations in prediction efficiency and accuracy, which fails to take into account the characteristics of the time dimension of speed data. This paper proposes an Long-Short Term Memory(LSTM) vehicle speed prediction model based on heuristic adaptive time-span strategy. The model mainly includes three parts: 1. In view of the instantaneity of the time series, we add weights to the input data, increase the weight of the data near the prediction point, and accelerate the convergence speed and accuracy of the model. 2. Simulated annealing algorithm is adopted to adaptively select the most appropriate time span for the current data. Compared with the traditional vehicle speed prediction model, this approach does not fix the time span and has better data universality. 3. The basic unit of the model is the LSTM model. The time series model is used to make prediction of speed, which is in line with the law of speed data. Validation of the model using driving data from ten vehicles over a 1-year period reveals that the LSTM speed prediction model based on a heuristic adaptive time-span strategy exhibits impressive accuracy and outperforms existing state-of-the-art machine learning models.

INDEX TERMS Automotive energy efficiency, vehicle speed prediction, machine learning, heuristic algorithms, neural networks.

I. INTRODUCTION

With the development of the social economy and technological progress, ground transportation plays an increasingly important role in ensuring the normal operation of the social and economic system. However, the rapid development of surface transportation has also brought about many problems. According to statistics, major cities in the United States lose \$47.5 billion annually due to traffic congestion, and up to 14.35 billion liters of fuel and 2.7 billion hours of work are wasted each year due to traffic congestion, and these figures keep growing at a rate of 5-10% per year [1]. In the UK,

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energy wastage due to traffic congestion will reach £1 billion per year. Government departments expect that this cost will double in the next 30 years and that environmental pollution will worsen [2]. In light of these facts, the issue of energy efficiency and safety of vehicles has attracted increasing attention from scholars around the world, and the related technologies have also been researched with a growing trend.

Vehicle speed prediction refers to the prediction and estimation of the future speed of a vehicle [3]. Vehicle speed prediction is one of the important components of automotive energy efficiency and safety research. For new energy vehicles, speed prediction can also be used for predictive control to improve vehicle energy economy and service life. In the field of new energy vehicles, the energy management of the vehicle directly affects the life and mileage of the vehicle, and the vehicle speed is the main direction of new energy vehicle management. If the vehicle speed can be accurately predicted to provide the most energy-efficient output conditions for the energy supply device of new energy vehicles, the mileage of the vehicle will be greatly improved and the waste of resources will be reduced [4]. Therefore, the study of vehicle speed prediction has important theoretical value and wide application prospects for new energy vehicles.

With the widespread application of computer- and communication-centered information technology in the field of vehicle control as well as prediction, and the research results of big data and machine learning accumulated over the past years, data-driven DL models have great potential for understanding speed prediction and can improve prediction capabilities. Such models are trained using vehicle travel data and can accurately and efficiently handle the relationship of prediction influence factors with high adaptability and portability [5].

Currently, machine learning models for vehicle speed prediction mainly include neural network models such as spatial models (ANN [6], DNN [7]) and temporal models (RNN [8], LSTM [9]). Artificial neural networks (ANN) also have unique advantages in handling a large number of parameters for vehicle speed prediction due to their complex network structure formed by interconnecting a large number of processing units (neurons). Fabritiis et al. [10] based on real-time floating car data (FCD), two algorithms based on artificial neural networks (ANN) and pattern matching, respectively, to predict online the average speed of the target road section for 5-10 steps or 15-30 minutes from the average speed of the current and neighboring road sections at 3-minute intervals, and finally use the prediction model to provide real-time traffic speed information for the Italian. Deep neural networks (DNNs), on the other hand, have multiple nonlinear mapping feature transformations that can be fitted to highly complex functions. This satisfies that the parameters of vehicle speed prediction are nonlinearly transformed features, so DNN is also suitable for vehicle speed prediction. Park et al. [11] mainly introduced a traffic model for vehicle speed prediction by DNN, which has 12 subneural networks, including both congested and non-congested traffic levels, each divided into 6 time intervals, and the upper limit of prediction is 30 minutes in the future. The results show that the longer the prediction interval, the better the prediction results are in the non-congested traffic situation, while the congested situation has a larger error when the speed fluctuates a lot.

Although some scholars have already done research on machine learning with vehicle speed prediction as the main focus, and good results have been achieved under certain conditions and situations. However, the above-mentioned literature does not cover in short-term prediction, for example, the models proposed by Lukas et al. [12] and Liu et al. [13] are neural network vehicle speed prediction models built with specified road section data, and the models are highly dependent on the road sections. If the road section is changed for prediction, the adaptability of the network will be reduced and the accuracy of vehicle speed prediction cannot be guaranteed. The application is not conducive to generalization under the premise of requiring accuracy, and the scope of use will be limited. Huang et al. [14] build neural networks based on work condition classification without time and space constraints. However, the article focuses on the benefits of analyzing the work condition classification, which is only divided into four work conditions. The average vehicle speed in the next 50 seconds is predicted under the same network structure without involving specific details of the vehicle speed variation or optimizing the network structure for each working condition. In addition, the speed predictions made in the above literature are based on the average speed of road sections or time periods. In addition, the speed predictions made in the above literature are based on the average speed of a road segment or time period, which obviously cannot meet the requirements for future stochastic continuous speed prediction, while the LSTM model is the model used to predict continuous time data [15]. From the perspective of time span, it is also questionable whether the same time span can meet the prediction requirements for predicting the speed of multiple future time periods, so it is necessary to establish an LSTM speed prediction model based on heuristic adaptive time span strategy.

This paper aims to solve the problem of short-term continuous vehicle speed prediction for automobiles, and establishes an LSTM vehicle speed prediction model with heuristic adaptive time span strategy based on the statistical basis of new energy vehicle driving cycle data. The model predicts the future continuous 30-second vehicle speed. The advantage of this model is that it is not constrained by road sections nor time span. The number of network layers, the number of nodes per layer, the activation function and the training function are included in the building process of the speed prediction model. The network structure is modified by the training and testing results of the model to finalize the network structure and predict the vehicle speed. Another advantage of the optimization algorithm studied in this paper is that it can solve the problem that different time

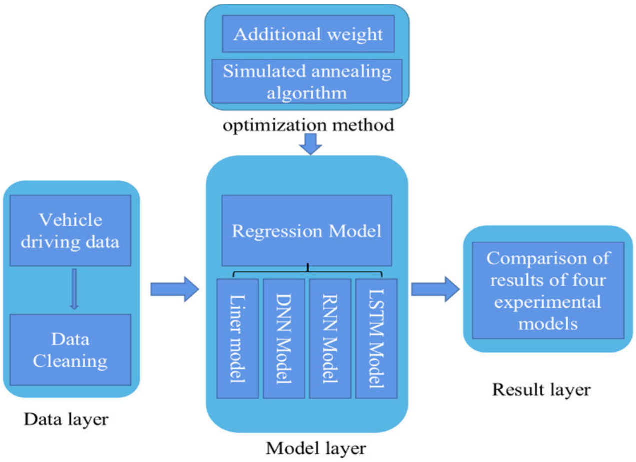

FIGURE 1. The overall flow chart of the experiment.

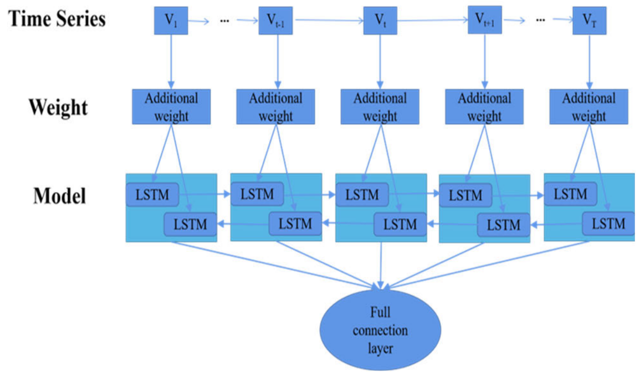

FIGURE 2. Diagram of LSTM model based on heuristic adaptive time span strategy.

intervals within a fixed time span selected by the traditional regression model for predicting vehicle speed have different effects on the prediction results but with the same weights, which leads to too low prediction accuracy or poor model generalization ability. This study proposes the design of additional weights to the input data, which solves the problem well and provides a new idea for the subsequent increase of time span to do speed prediction. Finally, based on the above study, we present the LSTM speed prediction model based on heuristic adaptive time span strategy. An improved simulated annealing algorithm is used to optimize the input time span of the LSTM neural network speed prediction model, so that the model can find the optimal time span for warp prediction autonomously. And the improved model is used for vehicle speed prediction, and the prediction results are compared with the unoptimized results and the results optimized by other neural network algorithms to directly improve the accuracy of the prediction.

II. MODEL DESCRIPTION

Figure 1 shows the overall structure of the algorithm.

As shown in the figure, our experiment is divided into four parts. The first part is the data layer, which mainly includes the introduction data and data processing. Detailed operations such as parameter selection and data pre-processing will be described in Part III A-C.

The second part is the model layer, which mainly includes all the models involved in our experiments (Liner, DNN, RNN, LSTM). In the subsequent a-d the four regression models are mainly described in detail and the inputs and outputs of each model are elaborated as a comparison with our optimized models. Among them, the LSTM model is the main model in this paper.

The third part is the optimization part, which is mainly optimized from two aspects. One is to weight the data to solve the problem that long time span affects the accuracy of the model. The other is to adapt the time span by simulated annealing algorithm to solve the problem that different data need different time spans for speed prediction. For time series data, the closer the data is to the predicted time, the more accurate the prediction will be, and the greater the weight will be. From the Weight layer in Figure 2, we have weighted the input data, as shown in formula (1):

$$y_i = \frac{\tanh\frac{i}{N}}{\sum_{j=1}^{N}\tanh\frac{j}{N}} \times y_i \tag{1}$$

where N represents the length of the time span and i represents the sequence number within the time span. y_i represents the data value of the current sequence number. Where tanh is the hyperbolic tangent function, we take the interval of the function whose definition domain is on [0, 1], and the closer to 1, the larger the function value. Then the closer to the prediction time of the input variables, the larger the weights will be. After weighting processing, the proportion of values close to the predicted data will be larger, and vice versa. This solves the problem that values far from the predicted data interfere with the prediction accuracy, and provides the possibility to expand the time span, find the optimal time span, and predict the vehicle speed for a long time.

For the problem of speed prediction time span selection, previous regression models use the same time span to simulate the temporal relationship between vehicle speed and predictors, ignoring the variation of different time spans on the relationship between vehicle speed and predictors, which has some limitations in reflecting the time span variability of vehicle speed. In order to overcome the above limitations, this paper proposes a time span optimization method based on the simulated annealing algorithm, which uses a simulated annealing algorithm to deal with time span predictors. The simulated annealing algorithm is derived from the solid annealing principle, which is a probability-based algorithm that heats up the solid to a sufficiently high temperature and then allows it to cool down slowly. The objective function of the simulated annealing algorithm in this paper is the LSTM model, and the variable is the time span. The accuracy of the LSTM model differs greatly for different time span inputs. The simulated annealing algorithm starts from a certain time span with low accuracy, and along with the decreasing temperature (time span) parameter, it combines the probabilistic jump property to find the global optimal solution of the objective function (RMSE) in the solution space randomly. Assuming that the previous state is x(n), the system changes its state to x(n+1) according to the RMSE (gradient descent, energy of the previous section). Correspondingly, the energy of the system changes from E(n) to E(n+1). Define the acceptance probability P of the system changing from x(n) to x(n+1) as:

$$\mathrm{P}=\begin{cases}1, & \mathrm{E}\left(\mathrm{n}+1\right)<E\left(\mathrm{n}\right)\\ \mathrm{e}^{-\frac{\mathrm{E(n+1)-E(n)}}{\mathrm{T}}}, & \mathrm{E}\left(\mathrm{n}+1\right)\geq \mathrm{E}\left(\mathrm{n}\right)\end{cases} \tag{2}$$

$$\mathrm{E(n)}=\mathrm{RMSE(n)} \tag{3}$$

From equation (2), we can see that if the energy decreases, then this transfer is accepted (with probability 1). If the energy increases, it means that the system deviates further from the position of the global optimum. At this point the algorithm does not discard it immediately, but performs a probabilistic operation: First a uniformly distributed random number α is generated in the interval [0,1]. If α < P, such transfer is accepted. Otherwise, the transfer is rejected and goes to the next step, and the cycle repeats. Where P takes the amount of change in energy and T to determine the magnitude of probability P, so this value is dynamic. That is, in the local optimal solution can probabilistically jump out and eventually converge to the global optimum. Simulating the combinatorial optimization problem with solid annealing, the internal energy E is modeled as the RMSE value of the LSTM model and the temperature T evolves into the time span i, i.e., the simulated annealing algorithm for solving the combinatorial optimization problem is obtained. This solves the drawback of the traditional LSTM model with a fixed time span, so that the optimal time span can be found for different data. Algorithm 1 is the pseudo-code for the adaptive time span of the above simulated annealing algorithm.

Algorithm 1

Pseudocode for adaptive time span of simulated annealing algorithm
s:= s_0; e:= $E_{(s)}$// Set current state as s, and the energy as $E_{(s0)}$
k: =0// K is the number of evaluations
while k<k_{max} and e>e_{max}// If there is enough time(k isn't reach to k_{max}) and the result is not good enough(e is not low enough), then:
s_n := neighbour(s)// Disturbance produces new s_n
e_n :=$E_{(sn)}$// The energy of $s_n$is $E_{(sn)}$
if random()<P(e,e_n,temp(k/k_{max})) then// Decide whether to generate a new s_n
s:= s_n; e: = e_n// Accept the new s_n
k: = k+1// Assessment completed, k increased by 1
returns//return to s

The fourth part is the result layer. The result layer is mainly for calculating errors, such as root mean square error (RMSE). RMSE represents the prediction volatility capability, which can reflect the accuracy of most regressions. Equation (4) is the definition criterion for this parameter.

$$RMSE == \sqrt{\frac{\sum_{i=1}^{N}\left(y_i-\hat{y}_i\right)^2}{N}} \tag{4}$$

where y_i is the real value of the data set at moment, and is the DL predicted value at moment. The smaller the RMSE, the better the predictive power of the model. All variables are standardized to reduce the impact of absolute scale. The experiment was conducted on a server equipped with Intel Core i5-9400 CPU, 2.60 GHz RAM and a GeForce RTX 2060 GPU, with an integrated development environment Pycharm 2018.1.4. Pytoch is the back-end of the experimental environment.

A. LINER MODEL

The linear regression model is a basic linear regression model and one of the most fundamental regression models. It can fit the most appropriate straight line from enough samples. In the contrast experiment, the input of the prediction model is a continuous time series of 10000 seconds, including 7 characteristic parameters. Therefore, the input size of the prediction model is 10000 × 7, and the output is the speed of the next 30 seconds with the size of 30 × 1. Since speed prediction is a regression task, in order to fairly compare the prediction performance of all regression models, all top layers are changed from Softmax loss layer to Euclidean loss layer. According to the hardware conditions, we use the Adam optimizer to train the model by setting the number of iterations to 40 and the number of batch processing to 64.

B. DNN MODEL

Deep neural networks (DNN) are the foundation of deep learning. It can extract distinctive data features from enough samples. Like the Liner model, in the comparison experiment, the input of the prediction model is a continuous 10000-second time series, which contains seven characteristic parameters and outputs the speed value of the next 30 seconds. For the DNN model, the input layer corresponds to seven input features that do not need to undergo the nonlinear processing of the activation function. Each feature is input to the next layer of the neural network through different lines, i.e., different weights w. The output size is 120 × 7×9880, and each neuron in the next layer adds a bias term to the weighted sum of all inputs. The hidden layer uses the standard rectifier linear unit "ReLU" to activate the function, and finally outputs the speed value.

C. RNN MODEL

RNN (Recurrent Neural Network), which generally takes sequence data as input, effectively captures the relationship characteristics between sequences through the structural design within the network, and generally outputs in the form of sequences. The circulation mechanism of RNN allows the results of the previous time step of the hidden layer of the model to affect the output of the current time step as part of the input of the current time step (the input of the current time step includes the output of the hidden layer of the previous step in addition to the normal input). Thus, the speed change trend can be captured and then successfully applied to speed prediction. In the contrast experiment, the input variables are the same as those of the liner prediction model, and their shape is 10000 × 7. The dimension of each input time step is 120 seconds, and the predictor consists of 7 variables. The variables are the 120 × 7 characteristic graph. The output is the same as the prediction model based on DNN. For RNN-based prediction models, the hidden layer size is set to 100 × 120. Then, according to the output data of 120 seconds in succession, the predicted speed of the next 30 seconds is obtained through the whole connection layer.

D. LSTM MODEL

LSTM is a time cycle neural network specially designed to solve the long-term dependency of general RNN. It can make full use of the information before and after the sequence. In time series data, the output of the previous step can be used as input data, so the information of the previous period can be stored in the memory gate and further affect the next output. Therefore, it can capture the long-term change trend of speed, and then successfully apply it to speed prediction. In the experiment, the input variable is the same as the input variable of the RNN prediction model, and its shape is 10000 × 7. The dimension of each input time step is 120 seconds, and the predictor is composed of 7 variables. The variables are the size of 120 × 7 characteristic graph. The output is the same as the prediction model based on RNN. For the LSTM-based prediction model, the hidden layer size is set to 100 × 120. Then, according to the output data of 120 seconds in succession, the predicted speed of the next 30 seconds is obtained through the whole connection layer.

E. LSTM MODEL BASED ON HEURISTIC ADAPTIVE TIME-SPAN STRATEGY

Figure 2 shows the flow chart of the LSTM model based on the heuristic adaptive time span strategy. The first layer is the data input layer, and the input variable is the same as the RNN prediction model input variable, which is the time series data of a car in motion with shape 10000 × 7. Each input time step dimension is derived from the simulated annealing algorithm and the predictor consists of 7 variables, the variables are 120 × 7 size feature maps. The second layer is the weighting layer, which deals with the problem of reducing the accuracy of the model due to too long time span. The data is processed by the second layer, and the feature map size is still 120 × 7. The third layer is the main body of the model, LSTM model, which is good at dealing with continuous time data series, which is the same as our input data, so we choose LSTM model as the main body of our model. As shown in Figure 3, the structure includes input gate $\mathrm{i_t}$, forgetting gate $\mathrm{f_t}$ and output gate $\mathrm{o_t}$. The input gate is used to update the cell state. First the information about the hidden state of the previous layer and the feature values of the current input are passed to the sigmoid function. The value is adjusted between 0 and 1 to determine which information to update. 0 means not important and 1 means important. Next, the information from the previous layer of hidden states and the feature values of the current input are passed to the tanh function to create a new vector of candidate values. Finally, the output value of sigmoid is multiplied with the output value of tanh. The output value of sigmoid determines which information in the output value of tanh is important and needs to be retained. The output gate is used to determine the value of the next hidden state, which contains information from the previous input. First, we pass the previous hidden state and the current feature value to the sigmoid function, and then pass the newly obtained cell state to the tanh function. Finally, the output of tanh is multiplied with the output of sigmoid to determine the information that the hidden state should carry. The hidden state is then used as the output of the current cell, and the new cell state and the new hidden state are passed to the next time step. The function of the forgetting gate is to decide which information should be discarded or retained. The information from the previous hidden state is passed to the sigmoid function along with the feature value of the current input, and the output value is between 0 and 1, with closer to 0 meaning it should be discarded and closer to 1 meaning it should be kept. Long-term memory is achieved through these three gates, and the parameters in the LSTM structure are shown in Eq. (5)-Eq. (9):

$$\mathrm{f_t} = \sigma(\mathrm{w_{xf}} + \mathrm{w_{hf}h_{t-1}} + \mathrm{w_{cf}c_{t-1}} + \mathrm{b_f}) \tag{5}$$
$$i_t = \sigma(\mathrm{w_{xi}x_t} + \mathrm{w_{hi}h_{t-1}} + \mathrm{w_{ci}c_{t-1}} + \mathrm{b_i}) \tag{6}$$
$$o_t = \sigma(\mathrm{w_{xo}x_t} + \mathrm{w_{ho}h_{t-1}} + \mathrm{w_{co}c_{t-1}} + \mathrm{b_o}) \tag{7}$$
$$c_t = f \cdot_t \mathrm{c_{t-1}} + \mathrm{i_t}\cdot\mathrm{tanh}(\mathrm{w_{xc}x_t} + \mathrm{w_{hc}h_{t-1}} + \mathrm{b_c}) \tag{8}$$
$$h_t = o_t \cdot tanh(c_t) \tag{9}$$

In formula (5) - formula (9), $\mathrm{c_t}$ represents the cell state at the time of t, $\mathrm{h_t}$ represents the output of hidden layer, and $\mathrm{b_f}$, $\mathrm{b_i}$, $\mathrm{b_o}$, $\mathrm{b_c}$ represents offset. $\mathrm{w_{xf}}$, $\mathrm{w_{hf}}$, $\mathrm{w_{cf}}$, $\mathrm{w_{xi}}$, $\mathrm{w_{hi}}$, $\mathrm{w_{ci}}$, $\mathrm{w_{xo}}$, $\mathrm{w_{ho}}$, $\mathrm{w_{co}}$, $\mathrm{w_{xc}}$, $\mathrm{w_{hc}}$ represent weights, which are obtained through training. According to the constructed LSTM model, it is able to capture the long-term relationship of the features in the vehicle driving data. This helps to improve the model to judge the vehicle speed at the current moment based on the input at the current moment and the state at the previous moments, so the theory has a higher accuracy rate. In this paper, the LSTM model is used to process the vehicle driving information with temporal characteristics, combined with the whole connection layer in the neural network to fuse multiple features, which becomes the main body of this experimental model. The data is output to the hidden layer after a modified LSTM model, and each neuron in the hidden layer is weighted and summed over all inputs, plus a bias term. The hidden layer uses the default rectified linear unit ''ReLU'' activation function, and the data is passed through the hidden layer, resulting in a continuous velocity value.

III. SIMULATION AND RESULT ANALYSIS UNITS

A. DATA SOURCE AND SPAN SELECTION

The research data came from the experimental data of National Big Data Alliance of New Energy Vehicles (NDANEV). The data is the driving data of ten new energy vehicles within one year, which includes 6756825 data, and the data features include time, vehicle speed, total voltage, total current, SOC, drive motor speed, drive motor torque, drive motor temperature, drive motor controller temperature, motor controller input voltage, motor controller DC mother current, acceleration pedal stroke value, brake pedal status, which are 13 The first 10,000 items were selected for this experiment. The first 10,000 data are selected as training data and 10,000-12,000 data are test data for this experiment. Previous experiments limited the total length of the predicted output speed and the historical input speed of the neural network to a fixed time interval, such as a fixed time interval of 150 seconds. After selecting 60 seconds as the predicted output time length, the historical input vehicle speed time length is set to 90 seconds of the current experience. In other words, if the current moment is T, the historical input speed is the speed data from T-89 seconds to the T second, which means the sampling time length is 90 seconds. Unlike the previous ones, this paper makes an innovative effort to use the adaptive input vehicle speed time length to find the optimal time length to satisfy the best efficiency with the optimal accuracy.

B. CORRELATION ANALYSIS OF CHARACTERISTIC PARAMETERS

Correlation analysis refers to the analysis of two or more elements of variables that have correlation, so as to measure the closeness of the correlation between two variable factors. A correlation analysis is only possible when there is a certain association or probability between the correlated elements. This paper adopts the Pearson product moment correlation coefficient, which measures the correlation between two variables X and Y (linear correlation), with a value between -1 and 1. The Pearson correlation coefficient between two variables is defined as the quotient of the covariance and standard deviation between the two variables:

$$\rho(X, Y) = \frac{\operatorname{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y} \tag{10}$$

From the results of correlation analysis in Figure 4, we can see that the correlation coefficient matrix is symmetric, so we only need to find the characteristic parameters corresponding to the data with greater correlation in the data below the main diagonal. Some foreign scholars take the correlation coefficient of 0.3 and 0.5 as the limit. If the absolute value is greater than or equal to 0.3 but less than 0.5, it is considered to have moderate correlation. If the absolute value is greater than or equal to 0.5, it is considered to have high correlation. This paper also takes this limit as reference. From the figure, it can be seen that the seven parameters that have correlation with speed are voltage, drive motor speed, drive motor temperature, drive motor controller temperature, motor controller input voltage, accelerator pedal travel value, and brake pedal status. Seven parameters with high correlation with speed may cause the training speed of the model to decrease, but the accuracy of the model will be greatly reduced when we try to reduce the number of parameters. Therefore, in this paper, we still choose 7 parameters for model training.

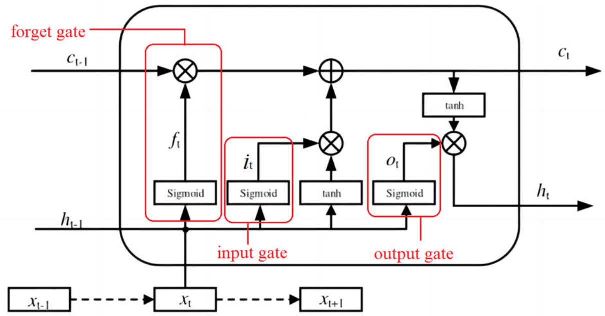

FIGURE 3. LSTM unit structure diagram.

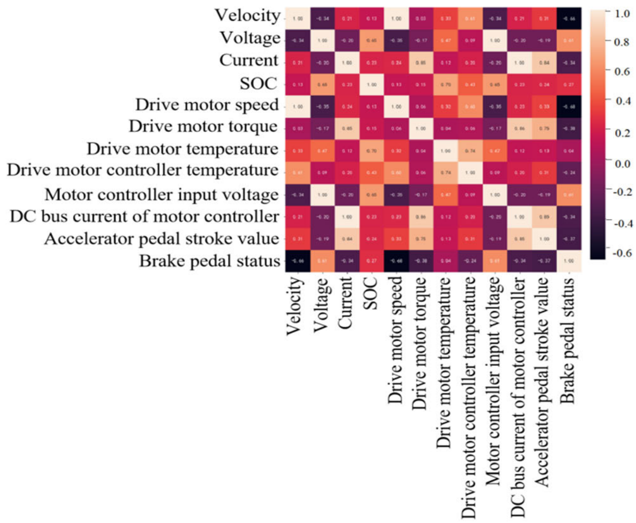

FIGURE 4. Parameter correlation analysis.

This paper analyzes the relationship between speed and voltage, drive motor speed, accelerator pedal travel value and brake pedal status, as shown in Figure 5. Figure 5 (a) shows the relationship between speed and brake pedal status. It can be seen from the graph that the speed is basically inversely proportional to the brake pedal status, and the speed increases fastest when the brake pedal status is 0, i.e. when the brake pedal is depressed. Figure 5 (b) shows the relationship between speed and accelerator pedal stroke value. When the accelerator pedal value is positive, the speed increases. When the accelerator pedal curve slope value is positive, the speed curve slope is large. When the accelerator pedal curve slope value is negative, the speed curve tends to be flat. When the accelerator pedal stroke value is 0, the speed decreases. Figure 5 (c) shows the relationship between speed and voltage. Like Figure 5 (a), speed and voltage are also

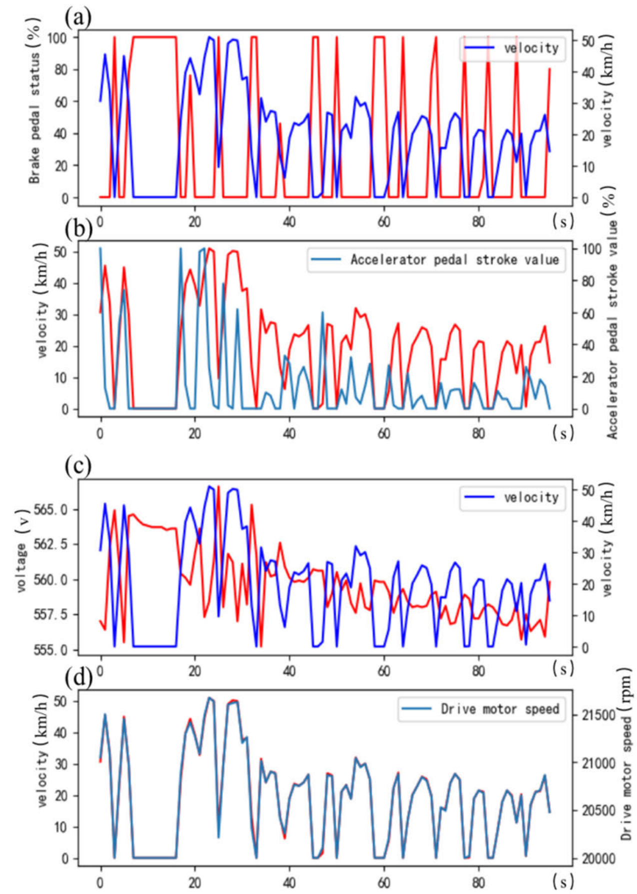

FIGURE 5. Time analysis of main parameters.

in a simple inverse relationship. However, when the voltage changes rapidly, the speed still keeps the original change rate, and the slope does not change. Figure 5 (d) shows the relationship between the speed and the speed of the drive motor. The speed refers to the vehicle driving speed, while the drive motor speed can be regarded as the tire speed, so it can be seen from the figure that the two are basically the same.

C. DATA PROCESSING

The time series data for vehicle speed are first screened to check data consistency and to deal with invalid and missing values. Excel is utilized to automatically identify each variable value that is out of range based on the defined range of values, and then normalize that data. Certain missing values are replaced with the average, maximum, and minimum values to achieve the purpose of purification.

D. COMPARATIVE ANALYSIS OF REGRESSION MODEL DATA

In this paper, the general speed prediction model (Liner, DNN, RNN, LSTM) and LSTM model based on input variable weighting strategy are used to predict the vehicle speed, and the experimental data are recorded. Table 1 shows the weighted and unweighted experimental results of

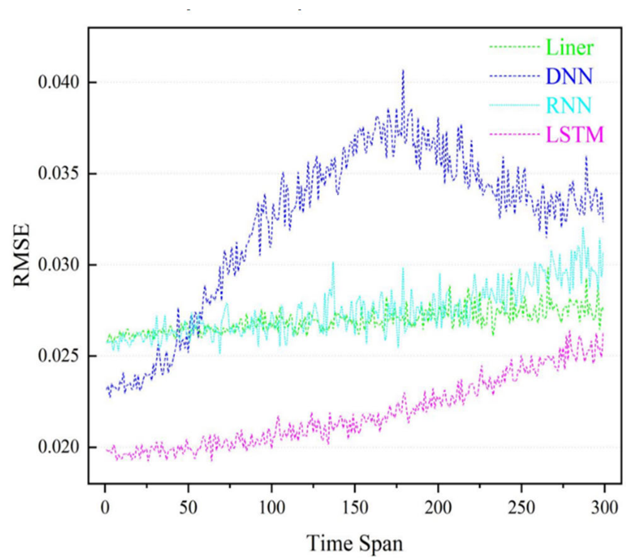

FIGURE 6. Comparison of results of four DL models.

TABLE 1. Weighted and unweighted experimental results of four DL models.

Model	RMSE	TimeSpan
Liner	0.0257	5
Liner+Weight	0.0255	15
DNN	0.0230	3
DNN+Weight	0.0210	13
RNN	0.0251	69
RNN+Weight	0.0246	15
LSTM	0.0192	26
LSTM+Weight	0.0190	63

the four regression models. The general regression models show good performance (0.0257, 0.0230, 0.0251, 0.0192), of which the general LSTM performs best. The LSTM model based on the input variable weighting strategy is particularly outstanding, with the RMSE of the optimal result of 0.019 and the time span of 63. Figure 6 shows the comparative analysis of four DL models. It is clear from the figure that when the time span is less than 50 seconds, DNN model and LSTM model perform better, with RMSE below 0.025, but the performance of Liner model and RNN model is slightly weak (RMSE above 0.025). However, when the time span is greater than 50s, all models show poorer accuracy. Among them, the LSTM model performs the most consistently among the four models although it decreases (up 15%), which highlights the fact that the accuracy of the DNN model decreases considerably (the slope of the RMSE results is about 1 between the time span 50s-180s). This indicates that without weighting the input data, the accuracy of different models decreases to different degrees as the time span increases. We assume that the reason for this situation may be due to the fact that the time in the front end of the time

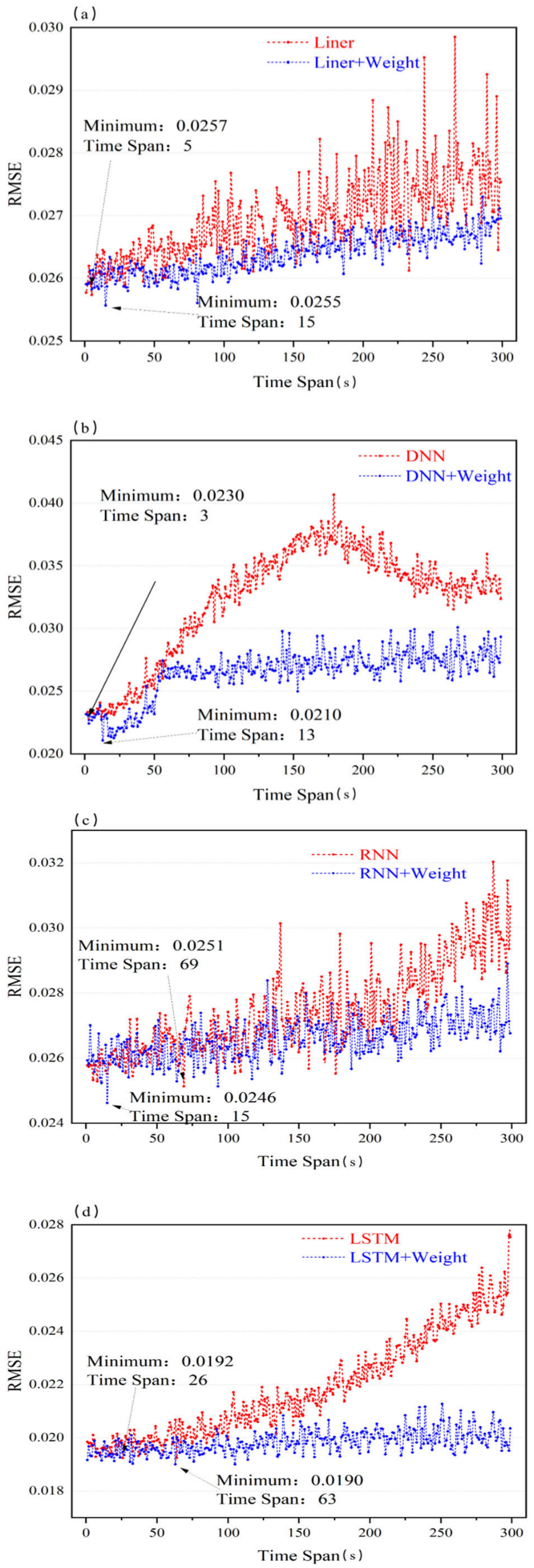

FIGURE 7. Comparison of weighted and unweighted results of all DL models.

horizon is too long apart from the desired prediction while the time horizon increases, resulting in a small impact of the

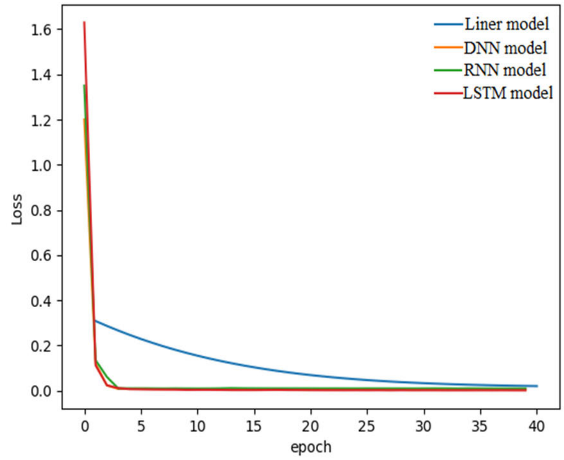

FIGURE 8. Convergence rate of four DL models.

TABLE 2. Comparative experimental results of LSTM model and LSTM model based on heuristic adaptive time-span strategy.

	RMSE	Time Span	Training Time
HATLSM model	0.0190	26	7.5hours
LSTM model	0.0190	26	22.1hours
Liner model	0.0257	5	15.7hours
DNN model	0.0230	3	17.3hours
RNN model	0.0251	69	20.9hours

variable values in the front end of the time horizon on the prediction.

However, the weights in the model are consistent with the weights at the end of the time span. Therefore, we believe that weighting the input data and reducing the impact of the variable value at the front of the time span on the prediction will improve this result. Figure 7 shows the results of our comparative experiment. For the four regression models, we have carried out weighted experiments and comparative experiments (time span: 1-300 seconds). Figure 7 (a) shows the weighted and unweighted experimental results of the input data of the Liner model. Figure 7 (b) shows the weighted and unweighted experimental results of the input data of the DNN model. Figure 7 (c) shows the weighted and unweighted experimental results of the input data of the

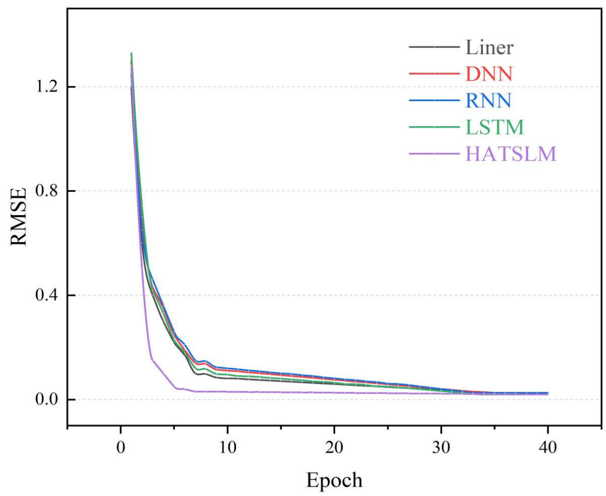

FIGURE 9. Comparison of training convergence speed of five models onvergence rate of four DL models.

RNN model. Figure 7 (d) shows the weighted and unweighted experimental results of the input data of the LSTM model. It can be clearly seen from the four figures in Figure 7 that although the accuracy of the experiment will still decrease with the increase of the time span when the input data is weighted, the growth rate of the four curves is below 20%. In particular, it can be seen from Figure 7 (b) and Figure 7 (d) that the experimental results of DNN model and LSTM model have improved significantly after the input data is weighted, When the time span of DNN model is 180 seconds, the test results are optimized by 50%, and LSTM model also has good results when the time span is greater than 120 seconds (RMSE is below 0.022). Although there is little improvement in the optimal value of the experimental results of the four DL models, this idea makes it possible to increase the time span prediction speed. Figure 8 shows the convergence rate of the four models. It can be seen from the figure that the convergence rate of the model in this paper is faster than that of the Liner model, and slightly faster than that of the CNN model and RNN model.

E. LSTM MODEL BASED ON HEURISTIC ADAPTIVE TIME-SPAN STRATEGY

It can be seen from Figure 7 that the accuracy of the four DL models, whether weighted or unweighted, is decreasing as the time span increases, so the traditional idea of fixed time span of regression model obviously can not make a good speed prediction. So, we propose LSTM model based on heuristic adaptive time span strategy (HATSLM), which uses simulated annealing algorithm to optimize the time span and automatically find the optimal time span. For different data sets, our model can adapt to the optimal time span and find the most suitable time span for the data set. Table 2 shows the running time comparison test results of the five models. Liner, DNN, RNN and LSTM use the exhaustive method to calculate all the results with a time span of 1-300 seconds. The other is the LSTM model based on heuristic adaptive time span strategy, which is used by us to find the optimal time span from 1s-300s. From Table 2, we can clearly see that the time required by our method is about one third of that of the traditional LSTM, and the accuracy is the same. This greatly improves the efficiency of finding the optimal time span.

Figure 9 shows the results of the convergence rate of the five models. The reference ordinate is RMSE. It can be seen from the figure that the HATSLM model converged in the fifth round, but the other four traditional regression models converged after the tenth round, which verifies that the training efficiency of the HATSLM model is higher than that of the traditional regression model.

IV. CONCLUSION

In this research project, a new adaptive model is proposed to do vehicle speed prediction based on a heuristic adaptive time span strategy, which breaks through the original concept of fixed time span - the LSTM speed prediction model. This model is trained to automatically find the optimal time span and accurately capture the transformed relationship between vehicle speed, time span and other predictors, overcoming the disadvantages of traditional DL models that waste efficiency and accuracy due to fixed time span. It is able to enhance the vehicle speed prediction performance of DL models with consistently more accurate results and higher efficiency. This study tested the speed prediction performance of relevant DL models (Liner, DNN, RNN, LSTM) for vehicle speed prediction on daily vehicle data. Then the improved LSTM model of this paper is compared with the commonly used DL models for vehicle speed prediction. The experimental results show that the LSTM prediction model can achieve a lower RMSE (0.0257, 0.0230, 0.0251, 0.0192) than other DL models (Liner, DNN, RNN) compared to the traditional DL models. The LSTM model improved by us, on the other hand, has similar results as the LSTM model with the same time span chosen (RMSE of 0.0190), but for different training data, our model can adaptively choose the optimal time span, which greatly increases the generalization ability of the model. In general, too small or too large time span will have a large impact on the speed prediction accuracy. Our model can determine the optimal time span faster and more accurately, which successfully overcomes the shortcomings of traditional DL models. It is expected that this paper can provide more novel ideas and methods for speed prediction models.

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