Proceedings of the 2025 SICE Festival with Annual Conference
September 9-12, 2025, Chiang Mai, Thailand

LSTM Encoder-Decoder model for Short-term Power Demand Prediction of Vehicles in Urban Driving Environment

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Abstract: With the development of vehicular network technology, the prediction of vehicle power demand has become significant in intelligent transportation systems and energy consumption optimization. However, due to the complexity of the traffic environment, prediction of short-term vehicle power demand with great accuracy faces challenge. In order to improve the prediction accuracy, this work proposes a LSTM Encoder-Decoder prediction model. The model extracts key features from input data through the encoder, and with the features, uses the decoder to generate future predictions of vehicle power demand. To validate the effectiveness of the model, experiments are conducted using a real-world dataset, and comparisons are conducted to the LSTM model. Experimental results show that the proposed prediction model has obvious advantages in both prediction accuracy and stability. Moreover, the work proposes a systematically evaluation and analysis on the impact of different feature sets on prediction performance.

Keywords: Short-term prediction, Encoder-Decoder architecture, Feature analysis, LSTM network.

1. INTRODUCTION

The driving range of electric vehicles (EVs) stands as one of the most critical concerns for users. By optimizing energy consumption to reduce energy usage per unit distance, the range on a single charge can be significantly extended, effectively alleviating users' "range anxiety." Given that the energy consumption of EVs is closely related to driving behaviors, accurately predicting short-term power demand has emerged as a key factor in energy optimization [1]. Short-term power demand prediction involves analyzing the vehicle's current state (such as speed and acceleration) and historical driving data, combined with traffic environment information (such as the behavior of leading vehicles, traffic signal status, and road gradient), to forecast future short-term acceleration changes using predictive models.

Prediction methods are commonly divided into two main categories: model-based approaches and data-driven techniques. Early research predominantly relied on model-based methods, which often adopted simplified assumptions, such as constant acceleration or constant speed [2], due to the lack of real-world data. However, these idealized assumptions frequently diverge from actual driving conditions, failing to accurately capture the complexity and dynamic nature of real driving behaviors. To address this limitation, subsequent studies have focused on simulating human driver pedal operations and developing advanced car-following behavior prediction models [3] based on microscopic traffic theory. These models better reflect the dynamic variations and uncertainties inherent in real-world driving scenarios. Furthermore, as a classic stochastic prediction framework, Markov Chain (MC) [4] not only predicts mean values but also characterizes the distribution of prediction errors, offering more comprehensive statistical insights into the results. This enhances the practicality and reliability of such models. Similarly, Moser et al. [5] utilized a conditional Gaussian model to predict vehicle speed changes over a 1-15 second horizon. By assuming known future traffic signal states in urban driving scenarios, the model achieved relatively accurate and reliable speed prediction result.

Data-driven prediction systems are inherently flexible, typically lacking fixed parameters or structures, with their performance heavily dependent on the characteristics of the input data. For instance, Liu et al. [6] conducted a comprehensive comparative study of various deterministic and stochastic time series prediction methods, revealing that under identical driving conditions, the Long Short-Term Memory (LSTM) method outperformed other algorithms, including the Autoregressive Moving Average (ARMA) algorithm and the Markov Chain (MC) model. Data-driven models often achieve high accuracy in speed prediction when ample training data is available. Lefèvre et al. [7] compared the performance of parametric and non-parametric models in predicting vehicle speed over a 1-10 second horizon. Their findings indicated that while simple parametric models excel in short-term predictions, more sophisticated models are necessary to enhance accuracy in long-term predictions. Olabiyi et al. [8] leveraged deep Recurrent Neural Networks (RNNs) to predict driver actions 5 seconds in advance. Similarly, Lemieux et al. [9] utilized deep learning networks to forecast future vehicle speed and trajectory. Zhang et al. The work [10] integrated Vehicle-to-Vehicle (V2V) and

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Vehicle-to-Infrastructure (V2I) communication technologies into vehicle speed prediction tasks. By incorporating communication data, they not only improved prediction accuracy but also developed an energy management strategy based on speed prediction, offering a novel approach to optimizing vehicle energy consumption. Sun et al. [11] achieved robust speed prediction performance across four standard driving cycles using Radial Basis Function Neural Networks (RBFNNs). Hellström et al. [12] explored stochastic methods for vehicle speed prediction. Jing and Filev [13] investigated the application of fuzzy Markov models and autoregressive models in speed prediction, providing valuable insights for enhancing traditional methods. Fünfgeld et al. [14] implemented vehicle speed prediction over a 1-30 second range using Monte Carlo simulations, showcasing strong adaptability in long-term sequence prediction tasks. T. Gaikwad et al. [15] developed an LSTM model using multi-source data from vehicle, ADAS, and vehicle-to-infrastructure. Experiments showed the full dataset achieved the lowest MAE with a 10-second prediction window. T. D. Gaikwad et al. [16] developed a model that predicts vehicle speed 10 seconds ahead using data from highway and urban/highway mixed driving cycles, then applied it to an optimized Energy Management Strategy algorithm to optimize engine control for improved fuel economy.

Given the high demand for accuracy in the practical application of vehicle power demand prediction, we propose a LSTM Encoder-Decoder vehicle power demand short-term prediction model. This model integrates multi-source data (such as vehicle speed, acceleration, traffic signal status, preceding vehicle behavior, etc.), where the encoder extracts key features from the input data, and the decoder generates future short-term power demand predictions. Furthermore, to further enhance the model's performance, we conducted in-depth experimental research to systematically evaluate the contribution of various feature groups in the dataset to prediction accuracy. Through quantitative analysis of the impact of each feature group, we aim to precisely identify the key factors influencing the prediction results.

The organization of this paper is as follows: Section 2 provides a detailed description of the problem background and introduces the collected dataset, which will be used for the training and validation of the LSTM Encoder-Decoder vehicle power demand short-term prediction model. Section 3 delves into LSTM Encoder-Decoder vehicle power demand short-term prediction model, including the principles of the LSTM deep neural network and the overall architecture design of the model. Section 4 explores the impact of different feature combinations on vehicle power demand through lag correlation analysis and prediction accuracy evaluation. Based on the optimal feature combination, the LSTM Encoder-Decoder vehicle power demand short-term prediction model is compared with the LSTM vehicle power demand short-term prediction model to assess its prediction accuracy. Finally, Section 5 analyzes the limitations of the LSTM Encoder-Decoder vehicle power demand short-term prediction and discuss potential improvements for future research.

2. PROBLEM STATEMENT AND DATASET DESCRIPTION

The objectives of this paper are to develop a LSTM Encoder-Decoder vehicle power demand short-term prediction model to support predictive control and reduce energy consumption. Additionally, we will systematically evaluate the impact of different feature sets on vehicle power demand prediction and conduct an in-depth analysis of the contribution of each feature to the prediction task.

To develop a LSTM Encoder-Decoder vehicle power demand short-term prediction model, this study employs the Benchmark Problem dataset [17]. This dataset offers a robust foundation for model training and validation by providing rich information on traffic environments. Generated using commercial traffic simulation software, the dataset emulates realistic urban driving scenarios as depicted in Fig.1. It encompasses a 1600-meter route featuring 26 traffic signals, significant road grade variations, and synthetic preceding vehicle interactions. Through ten replications of the data collection process along this route, the dataset systematically captures the combined effects of traffic light data, road slope, and vehicle-to-vehicle dynamics. The dataset contains both deterministic patterns and stochastic variations inherent in real-world driving conditions.

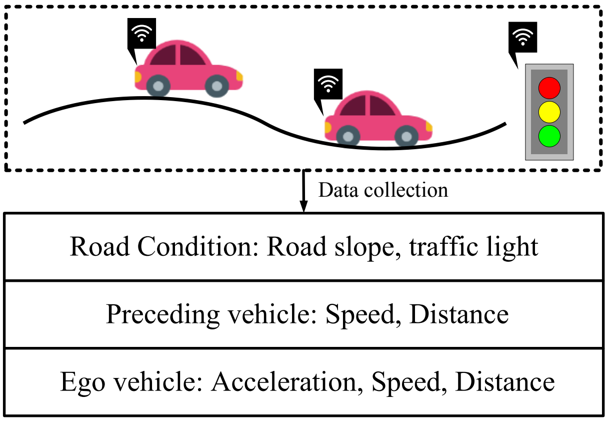

Fig.1 Urban driving environment.

Fig.2 shows the speed-time curves of the ego vehicle and the preceding vehicle. Both vehicles exhibit high-frequency speed fluctuations within the range of 0 to 20 m/s, indicating frequent acceleration and deceleration during driving. The speed variations of the two vehicles are highly consistent, suggesting that the ego vehicle's driving behavior is significantly influenced by the preceding vehicle.

Fig.3 shows the road slope-time curve. On the vertical axis, the gradient is positive for uphill sections and negative for downhill sections. The data reveal substantial fluctuations in road slope.

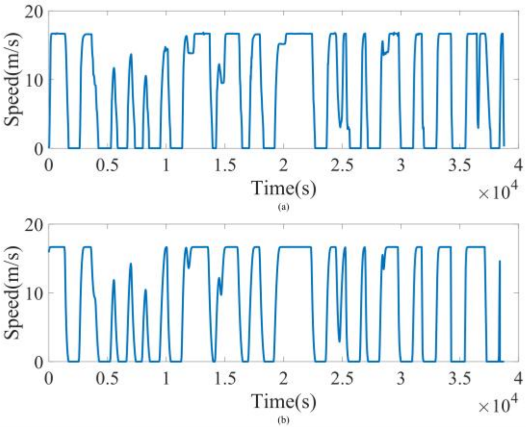

Fig.2 An example of the dataset speed (a. ego vehicle speed, b. preceding vehicle speed)

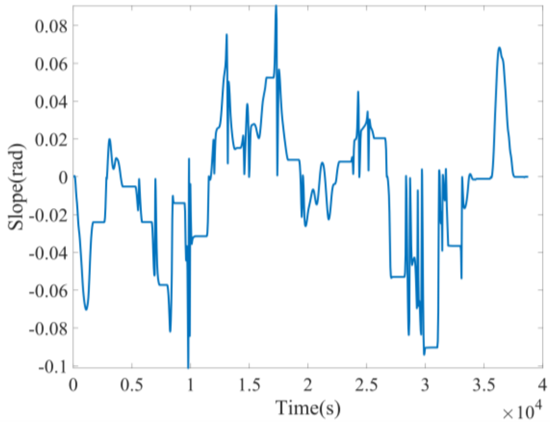

Fig.3 Instances of dataset road slope.

3. LSTM ENCODER-DECODER MODEL DEMAND PREDICTION

The proposed model adopts a hierarchical two stage architecture, effectively leveraging the sequential modeling capabilities of LSTM network.

In the encoder stage, the LSTM network processes historical input data layer by layer. By dynamically updating the cell state and hidden state via gated recurrent operations, ultimately generating latent feature representations that encapsulate historical information. These encoded latent features are then transferred to the decoder stage. In the decoder stage, the LSTM network initializes its state with the encoder's latent outputs. Combining them with the prediction result and road information, the decoder recursively computes and generates short-term power demand forecasts.

Fig.4 shows the LSTM Encoder-Decoder vehicle power demand short-term prediction model. The outputs of the encoder and the decoder can be formulated as follows,

$$c_T, h_T = f_e(c_{t-1}, h_{t-1}, X_e) \qquad \forall t \in [1, T] \tag{1}$$

$$y_d^t = f_d(c_{T+t-1}, h_{T+t-1}, x_d^{t-1}) \quad \forall t \in [1, N] \tag{2}$$

where f_e and f_d represent the encoder and decoder, respectively, T represents the length of the historical data, and N denotes the number of future steps to be predicted. When t = 1, c_{T+t-1} and h_{T+t-1} correspond to the y_e.

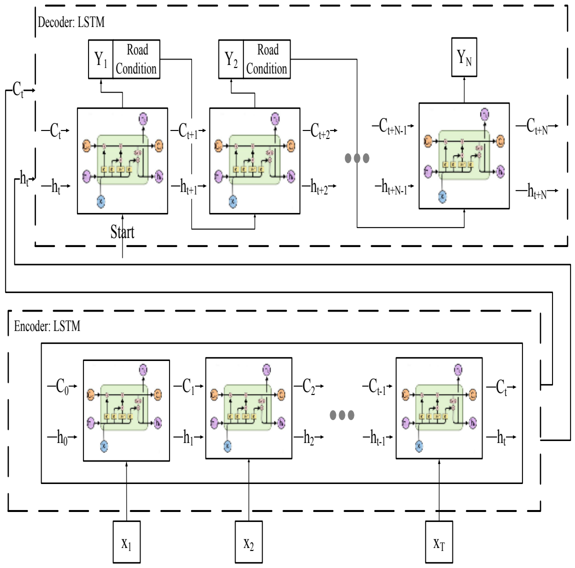

Fig.4 The Encoder-Decoder architecture.

The LSTM Encoder-Decoder vehicle power demand short-term prediction model consists of two outputs, specifically the encoder input X_e, decoder input x_d^t, encoder output y_e, and decoder output y_d^t.

The encoder input and output are as shown in the following equation,

$$X_e = [x_e^1, \cdots, x_e^{T-1}, x_e^T] \tag{3}$$

$$x_e^t = \left[a_{ego}^t, v_{ego}^t, s^t, d^t, p^t, r^t\right] \tag{4}$$

$$y_e = [c_T, h_T] \tag{5}$$

Where the encoder input X_e includes historical information from the past T steps, covering the ego vehicle's acceleration a_{ego}, speed v_{ego}, road slope s, relative distance to the preceding vehicle d, traffic light phase p, and remaining time r. The encoder output y_e includes the internal state c_T and the external state h_T at the current step.

The encoder input and output are as shown in the following equation,

$$x_d^t = [\ y_d^t, s^{T+t}, p^{T+t}, r^{T+t}] \tag{6}$$

$$y_d^t = \left[\hat{a}_{ego}^{T+t}\right] \tag{7}$$

where the decoder input x_d^t includes the predicted acceleration y_d, road slope s, traffic light phase p and remaining time r. When $t = 0$, the acceleration prediction value $\hat{a}_{ego}^T$ is the current acceleration a_{ego}^T. The decoder output y_d^t is the predicted acceleration $\hat{a}_{ego}^{T+t}$.

Conventional Recurrent Neural Networks (RNNs) struggle to model long-term dependencies due to gradient vanishing or exploding problems. LSTM networks effectively mitigate this limitation in RNNs by regulating information accumulation rates through gating mechanisms. Fig.5 shows the internal structure of the LSTM.

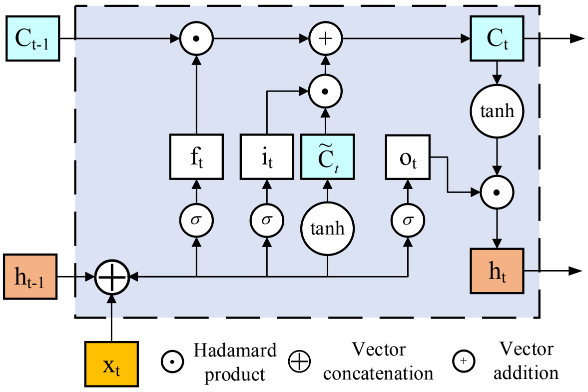

Fig.5 LSTM internal structure.

The forget gate f_t controls how much information from the previous time step's internal state c_{t-1} needs to be forgotten.

$$f_t = \sigma\left(W_f[h_{t-1}^T, X_t^T]^T + b_f\right) \tag{8}$$

where the input gate i_t decides controls how much information from the current time step's candidate state $\tilde{c}_t$ needs to be stored.

$$i_t = \sigma(W_i[h_{t-1}^T, X_t^T]^T + b_i) \tag{9}$$

$$\tilde{c}_t = tanh(W_c[h_{t-1}^T, X_t^T]^T + b_c) \tag{10}$$

where the output gate o_t controls how much information from the internal state c_t to the external output state h_t at the current step.

$$o_t = \sigma(W_o[h_{t-1}^T, X_t^T]^T + b_o) \tag{11}$$

$$c_t = f_t c_{t-1} + i_t \tilde{c}_t \tag{12}$$

$$h_t = o_t tanh(c_t) \tag{13}$$

where the matrices W_f, W_i, W_c, W_o and the vectors b_f, b_i, b_c, b_o denote the weights and biases for the forget gate, input gate, candidate state and output gate, respectively, σ and tanh serve as the activation function for these gates.

4. RESULT ANALYSIS

To systematically assess the prediction result, we introduce the assessment criteria: the Mean Squared Error (MSE). MSE measures the average squared difference between predicted and actual values, serving as an indicator of how much the model's predictions deviate from the true values. It is defined as,

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(a_{ego}^i - y_d^i\right)^2 \tag{14}$$

where n represents the number of samples. a_{ego}^i denotes the i^{th} actual value, and y_d^i denotes the i^{th} predicted value.

4.1 Feature analysis

The factors influencing vehicle power demand are categorized into ego vehicle, preceding vehicle and road condition. Therefore, a correlation coefficient analysis was conducted to study the relationships between vehicle power demand these three factors in Fig.6~8. Table 1 presents the composition of these feature groups and the impact of these features on prediction accuracy.

Fig.6 shows the correlation between ego vehicle and acceleration. The acceleration autocorrelation function exhibits a positive correlation, indicating the vehicle's motion state has high persistence. The lag correlation analysis between speed and acceleration reveals a negative correlation. When the vehicle at a high speed, the vehicle will trigger the braking strategy.

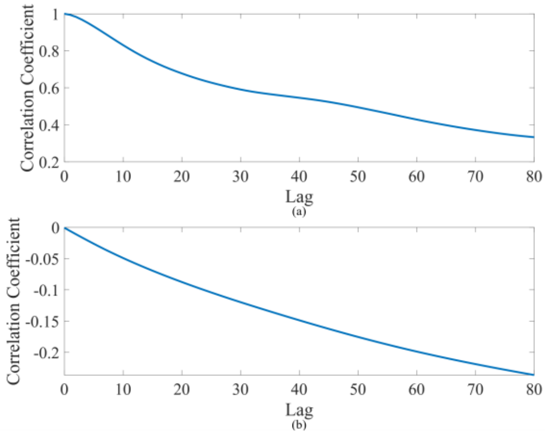

Fig.6 The correlation between the ego vehicle states (a. acceleration, b. speed) and acceleration.

Fig.7 shows the influence of the preceding vehicle on the ego vehicle's acceleration. The results indicate that both relative speed and relative distance are positively correlated with the ego vehicle's acceleration. When the relative speed or relative distance increases, the ego vehicle will adopt an acceleration strategy.

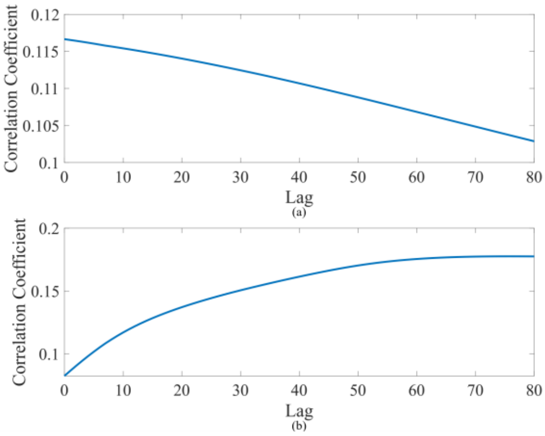

Fig.7 The correlation between the preceding vehicle states (a. relative speed, b. relative distance) and acceleration.

Fig.8 shows the impact of road condition on the ego vehicle's acceleration. There is a position correction between road slope and ego vehicle acceleration, indicating that the ego vehicle adopts an acceleration strategy under uphill condition. The traffic light phases were chosen during green light phases. There is a negative correlation between traffic light phases and ego vehicle acceleration, indicating that the ego vehicle acceleration when the remaining time of the green light phase decreases.

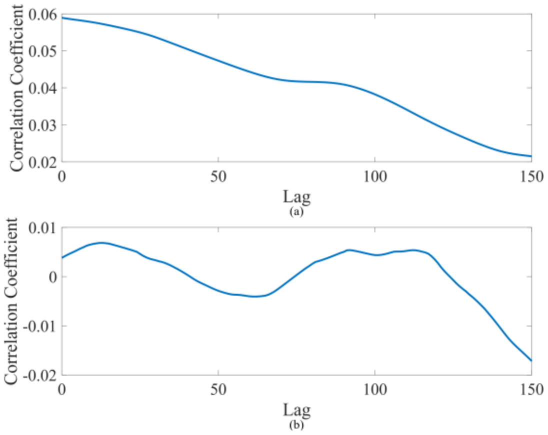

Fig.8 The correlation between the road condition states (a. road slope, b. traffic light) and acceleration.

After completing the lagged correlation analysis, we categorized the key influencing factors into five feature groups and conducted a comparative evaluation using MSE as the performance metric. Group A comprising fundamental vehicle motion parameters including acceleration and speed. Expanding upon Group A, Group B incorporates slope information to account for terrain variability. These groups further enhance Group B by integrating inter-vehicle interaction. Group C introduces relative distance, while Group D adds relative speed. Building upon Group C, Group E includes traffic light phase and remaining time data. The Testing results show that Group E achieves the best prediction performance.

Table 1 Effect of feature group on prediction performance.

Group	Feature	MSE
A	Acceleration, speed.	0.0602
B	Acceleration, speed, slope.	0.0593
C	Acceleration, speed, slope, relative distance.	0.0573
D	Acceleration, Speed, slope, relative speed.	0.0582
E	Acceleration, Speed, slope, relative distance, traffic light	0.0550

4.2 Rolling short-term vehicle power demand prediction evaluation

To evaluate model performance, a 100-meter segment was extracted from the test dataset. The number of neurons in both models is set to 64. The model takes driving distance as the benchmark scale, receiving historical data within a continuous 20-meter range as input and outputting predictive values for vehicle power demand over the next 20 meters of travel. A rolling short-term prediction approach was employed to assess the predictive performance of both the LSTM Encoder-Decoder model and standard LSTM model.

Fig.9 and Fig.10 present the performance of the LSTM model and the LSTM Encoder-Decoder model in rolling short-term predictions. When it comes to prediction error, the LSTM Encoder-Decoder model has a significantly lower error level compared to the LSTM model. Regrading prediction trends, the LSTM Encoder-Decoder model can precisely track the fluctuations of the target values. In contrast, the LSTM model shows a poor response to the changes in the target values. Considering both prediction error and trend tracking capabilities, the LSTM Encoder-Decoder model clearly outperforms the LSTM model in prediction performance.

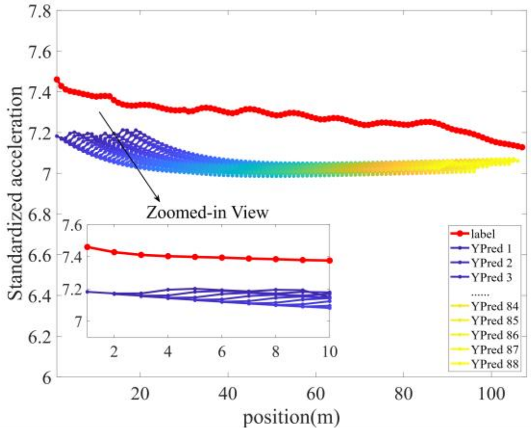

Fig.9 Rolling short-term prediction based on the LSTM model.

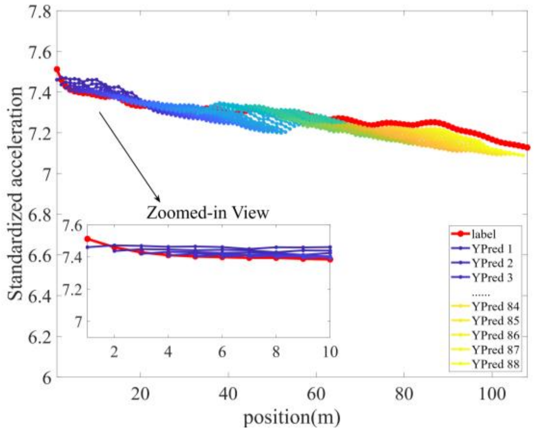

Fig.10 Rolling short-term prediction based on the LSTM Encoder-Decoder model.

A co-simulation platform was developed based on Simulink and SUMO (Simulation of Urban Mobility) to conduct real-time rolling prediction tests on the target model. During the testing, the model dynamically predicts vehicular power demand within a 21-meter range ahead at 1-meter intervals. Statistical analysis of multiple experimental datasets revealed that the model achieved an average inference time of 0.0059 s. Fig.11 presents the rolling prediction effect diagram during the vehicle's 3-meter driving process.

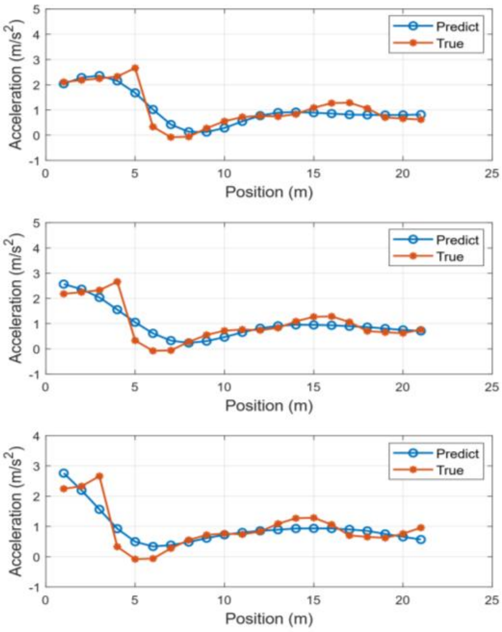

Fig.11 Real-time rolling prediction

5. CONCLUSION

This study proposes an LSTM Encoder-Decoder model for short-term vehicle power demand prediction to improve accuracy. Using a diverse driving dataset, we evaluated the model's performance through lag correlation analysis and MSE quantification. Compared to a standard LSTM model, the Encoder-Decoder model showed significantly higher prediction accuracy. However, experimental results show that error accumulation and lag phenomena still exist in short-term prediction. To address these issues, future research will explore the introduction of statistical features and extend the prediction horizon to further improve its performance.

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