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Multivariate Deep Learning Approach for Electric Vehicle Speed Forecasting

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Abstract: Speed forecasting has numerous applications in intelligent transport systems' design and control, especially for safety and road efficiency applications. In the field of electromobility, it represents the most dynamic parameter for efficient online in-vehicle energy management. However, vehicles' speed forecasting is a challenging task, because its estimation is closely related to various features, which can be classified into two categories, endogenous and exogenous features. Endogenous features represent electric vehicles' characteristics, whereas exogenous ones represent its surrounding context, such as traffic, weather, and road conditions. In this paper, a speed forecasting method based on the Long Short-Term Memory (LSTM) is introduced. The LSTM model training is performed upon a dataset collected from a traffic simulator based on real-world data representing urban itineraries. The proposed models are generated for univariate and multivariate scenarios and are assessed in terms of accuracy for speed forecasting. Simulation results show that the multivariate model outperforms the univariate model for short- and long-term forecasting.

Key words: Electric Vehicle (EV); multivariate Long Short-Term Memory (LSTM); speed forecasting; deep learning

1 Introduction

According to the United Nations and World Bank, urbanization is steadily increasing, and consequently, more than half of the world's populations will live in large cities. In developing countries, urbanization is even much higher than the worldwide average, with a high expected growth rate in the coming years. The increase in the number of people living in cities intensifies significant societal and environmental challenges, such as resource adequacy linked to air quality and pollution, access to reliable and sustainable energy, and efficient transportation and mobility solutions. For instance, transportation means are considered the principal source of greenhouse gas and the first polluter of urban zones. Moreover, the tightening regulations on CO_2 emissions and the high prices of fossil energy sources have driven governments to support the deployment of sustainable solutions.

Emerging technologies are often seen as an enabler to better cope with the development and societal challenges toward achieving sustainable development goals. For example, Intelligent Transport Systems (ITSs) and fleets renewable through the integration of a new generation of vehicles characterized by a low carbon footprint, such as full and Hybrid Electric Vehicles (EVs/HEVs), have been considered the most sustainable solutions for the mobility of goods and people. The proliferation of EVs in urban areas has accelerated because of recent advances in battery technologies. However, its exploitation faces several constraints, mainly those

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related to their limited driving range, the lack of charging stations, and the long charging time. These constraints represent a big challenge for the large deployment of EVs in transportation roads. Improving in-vehicle Energy Management (EM) is therefore in the keen interest and requires the development of predictive approaches.

Efficient EM in EVs is crucial to optimize battery-loading cycles and to overcome the lack of charging infrastructure. However, it is a complex task as it depends on many features: endogenous ones related to EV state, such as velocity, acceleration, comfort conditions, driver profile, and battery State of Charge (SoC) estimation; and exogenous ones related to the environment where EVs are evolving, such as road constraints, traffic, and weather conditions. Consequently, an accurate estimation of stored (in-vehicle) energy enables proper utilization for a long driving range through the establishment of an adapted driving strategy.

According to Vaz et al.[1], battery SoC estimation is important as it can be used to estimate the driving range based on residual energy. Nevertheless, SoC estimation is not sufficient as the residual energy can be consumed in different ways according to the driver preferences (speed, trip time, and comfort) and the driving condition changes. Consequently, the parameters influencing SoC estimation have been considered to develop efficient EM systems. Particularly, the vehicles' speed is considered one of the most important parameters for SoC estimation and mainly the one impacting the EM quality[2]. However, forecasting this feature is a challenging task as it fluctuates in a stochastic way and is fundamental for driving strategy adaptation.

In this research paper, we compare univariate and multivariate deep-learning-based models for speed prediction in EVs. The dataset used for model training is collected using the vehicle to everything (V2X) Simulation Runtime Infrastructure (VSimRTI) simulator based on real-world urban itineraries. The proposed data-driven approach relies on the use of a conventional univariate Long Short-Term Memory (LSTM) as a baseline approach for forecasting EV speed, and is compared with a multivariate LSTM model. The last method is built upon environment variables, such as speed limit, slope, and traffic conditions. Both methods have been tested for one-step- and multistep-ahead forecasting.

The remainder of this paper is structured as follows: Section 2 presents speed prediction approaches and ITS systems. Section 3 provides an overview of the proposed approach and prediction model (LSTM) preparation process. Section 4 presents the speed prediction results of the predefined simulation scenarios and a discussion about the accuracy of the proposed methods. The last section discusses the contribution of the paper and the perspectives of this work.

2 Related Work

The depletion of fossil resources has boosted the development of innovative technologies for transportation, which also stimulated the development of new techniques for improving the EM in new-generation vehicles, such as HEVs and EVs. In this context, early works were focused on the establishment of vehicle-specific models for energy efficiency improvement through the optimization of mechanical features, such as torque split[3]. However, increasing information on future driving conditions has opened up new fields of research for efficient EM and made predictive EM realistic[4].

EM is impacted by various factors, such as weather conditions, driver behavior, SoC, traffic conditions, and roads types and profiles. Thus, ensuring EM efficiency is a tedious task as the previous conditions are continuously changing. To alleviate the complexity of this task, it has been proven that the EM performance is closely linked to vehicles' speed. In this context, Li et al.[2] presented two types of methods for speed forecasting: model-based, parametric methods and data-driven, non-parametric methods. The first one consists of theoretical models based on parameter specifications for a specific vehicle. The second one covers speed forecasting methods, which are based on massive data analysis and processing. According to Rezaei and Burl[5], statistical methods, such as time-series forecasting methods, can be used for predicting the factors that are directly impacting the speed to achieve optimal energy control.

In adequacy with the previous classification, Cheng et al.[6] specified three classes of speed forecasting models. The first category, which is model-based one, relies on theories and expertise to design a conditioned model for EM strategies. These models lack generalization for other vehicles due to the intensive tuning process on a case-by-case basis. The second category covers data-driven methods, which exploit machine learning to build adequate models. The success of such an approach relies on the representativeness of the dataset and quality of the training process. The last category consists of hybrid models based on the combination of models and data-driven approaches to take advantage of both domains.

The abovementioned models have also been studied based on the forecasting horizons. According to Jiang and Fei[7], parametric models are not suitable for long-term speed forecasting. Moreover, tuning for a specific type of vehicle hinders their adoption for large-scale speed traffic within a heterogeneous fleet. Consequently, data-driven methods have seen a great interest for vehicle speed forecasting for their capacity in building accurate models based on a simplified well-founded training and validation process. Moreover, they take advantage of their ability to overcome the complexity of exploiting highly nonlinear factors impacting the speed feature. In this context, an Artificial Neural Network (ANN) has been used for speed prediction as it can take multiple inputs. Park et al.[8] proposed a composite ANN model based on pretrained models according to four urban road types. Cheng et al.[6] used road segmentation to improve speed forecasting accuracy. They proposed an adaptive neuro-fuzzy inference system based on big data deep learning to integrate historic driving data for speed forecasting. ANNs were also used by Yan et al.[9] to forecast the vehicle speed and investigate the impact of driving factors on speed prediction. The proposed forecasting model has been applied for routing selection and the deployment of intelligent traffic control.

Other research works have tackled ANN hybridization to improve models' forecasting accuracy. Jiang and Fei[7] proposed a two-level model that used ANN as the first model to forecast speed in road segments. This information is used as the input of a second model based on a hidden Markov model to build a relationship between the vehicle speed and traffic speed. The Markov model was also used for velocity forecasting based on the discretized Markov space that links the vehicle acceleration to its speed. Ma et al.[10] proposed an innovative application of a convolutional neural network using spatio-temporal images, which combines speed and vehicles' localization to deal with large-scale traffic speed forecasting.

In parallel to these advances, ITS techniques continue to progress with the deployment of low-cost sensors, allowing a massive data harvesting on cars and their surroundings. This development also allowed a better visibility on road traffic with real-time monitoring of endogenous and exogenous cars parameters, especially those related to their surrounding environment. In other words, ITSs have become essential in the modern transportation system. The increasing number of deployed sensors in roads has generated a huge amount of data, which can be used in different application scenarios related to data-driven ITSs (D^2ITS)[11]. For instance, vehicle speed forecasting is an important feature for ITS applications. It enables the establishment of an efficient vehicle EM[12], such as rerouting, vehicle charging schedule[13], traffic efficiency[14], and remaining driving range control[15]. However, as previously mentioned, speed forecasting is a tedious task as it is closely related to various factors.

Many ITS applications have focused on speed forecasting through the development of new models aligned with the aforementioned classification: model-based, data-driven, and hybrid models[16]. Liu et al.[17], for example, proposed a mesoscopic model based on gas-kinetic traffic modeling to predict speed, and they achieved interesting results by decreasing the Root Mean Square Error (RMSE) ranges for speed forecasting. However, such an application remains specific to the study case and lacks a generalization as it requires intensive modification and calibration[18]. Unlike the last model, data-driven methods are easy to build, because they do not require any calibration or modification. Hybrid approaches take advantage of both models, but their accuracy depends on the quality of the dataset used for models' training[19].

In this study, we put emphasis on data-driven approaches for speed forecasting using univariate and multivariate techniques. We propose an LSTM-based model, which is trained on the basis of a dataset generated by a traffic simulator. The model was built upon real-world urban itinerary data and calibrated using validated urban traffic profiles. Simulations were conducted, and results are reported here to assess the efficiency of the model in terms of accuracy for short- and long-term speed forecasting.

3 Tool and Methodology

3.1 VSimRTI simulator

The dataset used for model training, as stated above, was collected from real-world urban itineraries using the VSimRTI simulator. VSimRTI is a comprehensive framework used for cooperative ITSs. It allows easy integration and exchange of existing simulation tools by combining them for a realistic development of applications. Examples of these tools are related to the presentation of vehicular traffic, emissions, wireless communication (cellular and ad hoc), driver behavior, and the modeling of mobility applications, including electromobility (EV model). VSimRTI uses the federate-ambassador concept inspired by the concept of high-level architecture. Using this concept, it is possible to couple different simulation tools with a remote control interface. For instance, attaching an additional simulator only requires the implementation of an appropriate ambassador interface and the possibility of executing its specified commands.

For traffic simulation, VSimRTI[20] uses Simulation of Urban MObility (SUMO)[21,22], which is a highly portable, microscopic, and continuous traffic simulation package designed to handle large networks. It also provides several tools and applications to help prepare a simulation scenario based on real-world data, e.g., netconvert to import and create road networks from OpenStreetMap (OSM), OpenDrive, or others, and dfrouter to generate routes and more. Since SUMO is a microscopic simulator, each vehicle and its dynamics are modeled individually and can be configured using specific configuration files to mimic real traffic scenarios as closely as possible. VSimRTI also uses OMNET++ and ns3 to simulate networking and vehicular communications, e.g., vehicle to vehicle and vehicle to infrastructure. Furthermore, it allows the development of custom applications via its Application Programing Interface (API), which can be deployed into the vehicle. These applications can be used for V2X communication, vehicle data gathering, and rerouting, among others.

3.2 LSTM

LSTM has been proposed to improve the conventional Recurrent Neural Net (RNN) through the integration of new gates, with the main aim of allowing a better control over the gradient flow and a long-time preservation of dependencies[23]. For this purpose, each LSTM cell, as depicted in Fig. 1, was enriched by three gates controlled by a sigmoidal layer generating values between 0 and 1 and depicting the contribution of each cell[24]. The first one, forget gate, depicts the amount of information to be forgotten by the LSTM cell. It takes the output of the last cell $\boldsymbol{h}_{t-1}$ and the value $\boldsymbol{x}_t$ as the input and outputs a number between 0 and 1 for each number in the cell state C_{t-1}. A value of 1 represents that the number in the cell state will be kept, and a value of 0 means that it

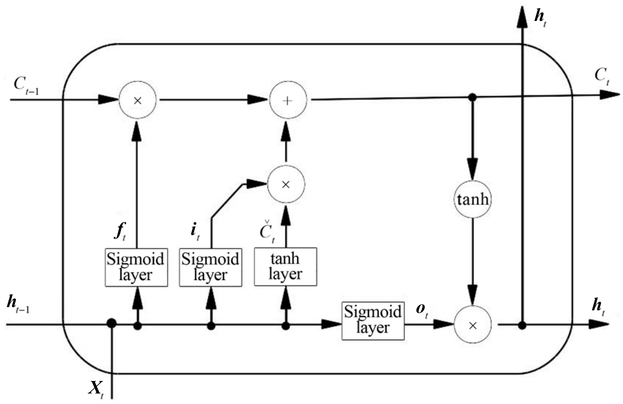


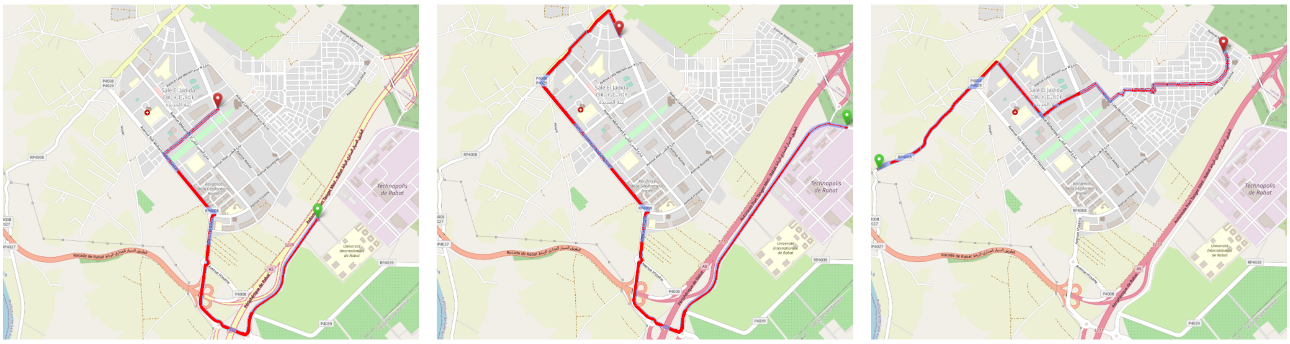
Fig. 1 LSTM gate.

will be rejected. The forget gate's activation vector $\boldsymbol{f}_t$ is processed as follows: $\boldsymbol{f}_t = \sigma(\boldsymbol{W}_f \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \boldsymbol{b}_f)$, where $\boldsymbol{W}_f$ represents the weight and $\boldsymbol{b}_f$ represents the bias, which are learned during the training process. The second one, the memory gate, allows controlling the data to be modified and the new values that should be stored in the cell memory. This gate is composed of two layers, a sigmoid layer called the input gate layer, which is responsible of deciding the values to be updated, and a tanh layer that generates a new candidate values $\tilde{C}_t$ to be added to the state C_t. The state C_{t-1} is then updated to a new state C_t as follows, $C_t = \boldsymbol{f}_t \times C_{t-1} + \boldsymbol{i}_t \times \tilde{C}_t$, where $\boldsymbol{i}_t$ is the input/update gate's activation value (computed by $\boldsymbol{i}_t = \sigma(\boldsymbol{W}_i \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \boldsymbol{b}_i)$ and $\tilde{C}_t$ is the cell input activation value, computed by $\tilde{C}_t = \tanh(\boldsymbol{W}_c \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \boldsymbol{b}_c)$. The third one, the output gate, decides about the result provided by each cell based on its state and the stored data. At this stage, the output $\boldsymbol{h}_t$ is based on the cell state after filtering its values by a sigmoid layer and multiplied with the tanh of the C_t as follows, $\boldsymbol{h}_t = \boldsymbol{o}_t \times \tanh(C_t)$, where $\boldsymbol{o}_t$ is the output gate's activation value. This value is computed by the following, $\boldsymbol{o}_t = \sigma(\boldsymbol{W}_o \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \boldsymbol{b}_o)$. C_t and $\boldsymbol{h}_t$ were then fed to the next cell with the input value $\boldsymbol{x}_{t+1}$ to output the value of $\boldsymbol{h}_{t+1}$.

3.3 Methodology

Many simulations have been conducted to elaborate the dataset, which is generated using the VSimRTI simulator. The algorithm is then trained upon these data, and the generated model is used to forecast the vehicle speed in the next simulation. Figure 2 shows three urban itineraries in Sala Al Jadida city, Morocco, which are used in the simulation.

Each trajectory starts from the green marker and ends in the red marker. The preparation of the simulation is



(a) (b) (c)

Fig. 2 Three itineraries used in the simulation.

performed through the following steps: (1) the map of the city is downloaded from the OSM website and then converted to the SUMO format; (2) the road network is generated using the SUMO tools; (3) various itineraries are generated and assigned to different vehicles; (4) a custom application is developed using Java to collect the vehicle data in which the application is deployed; and (5) different vehicle traffic are generated (14 EVs with an appropriate number of normal vehicles to simulate the low, medium, and heavy traffic).

After several simulations, the collected dataset is then prepared and used to train the LSTM model. The dataset mainly contains the following information: (1) the timestamp of the simulation, (2) ID of the road taken by the vehicle, (3) maximum speed in a specific segment of the road (this information is given by OSM), (4) actual speed of the vehicle, (5) road slop, (6) actual vehicle acceleration, (7) type of road (i.e., urban, highway), (8) battery SoC, and (9) traffic condition (the number of vehicles in a specific road segment).

It is worth noting that SUMO uses Krauss model[25] to determine the actual speed of the vehicle. It is considered a car-following model, which is based on the safe speed. This model tries to adapt the speed of a given vehicle according to the speed of the vehicle ahead. Thus, each vehicle tries to keep a safe distance. As the safe speed depends on the speed of the leading vehicle, it can exceed the speed limit in the actual road segment. To overcome this problem, the SUMO simulator takes the minimum speed between the safe and limit speed as the actual vehicle speed. OSM does not include information about the elevation, which makes it impossible to get the slope of a given road segment. To include this information, SUMO uses the SCENARIO-CONVERT tool, which can extract the elevation information from an SRTM file and add it to the OSM file.

For the traffic condition, the simulator does not provide any information about the number of vehicles in a segment of the road at a given instance. To overcome this issue, we developed a Java program combined with the simulator API and embedded it into all vehicles. This application retrieves the ID of the segment and the simulation timestamp and then saves them as a log file before sending them to the server. Afterward, once the data are received, a server-side application sums the vehicle count in a road segment at a given time. The resulting data are integrated to enrich the dataset used for the LSTM model training.

As previously stated, we prepared two LSTM models: the first one with a multivariate input and the second one with a univariate input. Both LSTM models generate the vehicle speed as the output. For the first model, the dataset contains the timestamp, road ID, maximum road speed, actual speed, slope, type of road, and traffic conditions. The second model is trained using a dataset built upon simulation timestamps and EV speed. Fourteen EVs are used in the following steps: We split the dataset into the training part using data generated by 10 EVs, and used the data generated by the remaining four vehicles as the test part. The two models are then used to forecast the vehicle speed. As the simulation is started, the Java application deployed in each EV gathers the data and sends them to the server, in which the LSTM algorithm is launched. As the algorithms get the data, they forecast the next speed values for predefined forecasting horizons, e.g., 1, 60, or 120 steps. The results are then saved into a CSV file for accurate estimation and further processing.

To ensure the two algorithms are executed in the same conditions, in the first simulation, the data generated by the four EVs are saved into a CSV file, and then a program is developed, which reads the data of a given vehicle from the CSV file and sends it again to the server. Consequently, we guarantee the use of the same data stream for both LSTM models. On the server side, we first launch the algorithm, load the univariate model, and then forecast the speed of one of the four vehicles. Then, we launch the algorithm again, load the multivariate model, and forecast the speed of the same vehicle. This process is then repeated for the three remaining vehicles and for different forecasting horizons.

4 Result and Discussion

Figure 3 depicts the EV speed forecasting results for the univariate LSTM model. The dashed black line represents the real data from the test vehicle, whereas the solid red line represents the forecasted data. Figure 3 shows that the one-step-ahead forecasting model efficiently predicts the vehicle speed, but the accuracy decreases for the multistep forecasting horizons (i.e., 60 and 120 steps). Therefore, the univariate LSTM model shows its limit for large-horizon forecasting. This limitation is owing to the dependency of speed to changes in other parameters, which are not used in this baseline approach.

Figure 4 illustrates the forecasting results provided by the multivariate model. Here the multivariate model can accurately predict the speed for all tested forecasting horizons. This model considers some factors that affect the speed prediction, such as road type, traffic condition, and road slope. To describe the driver behavior, the SUMO simulator allows giving a parameter in the configuration file related to the vehicle. This parameter remains constant during the simulation, and it will not affect the forecast if included in the training process.

For comparison, we calculated the RMSE and Symmetric Mean Absolute Percentage Error (SMAPE) errors. Tables 1 and 2 represent, respectively, the RMSE and SMAPE error metrics for the study forecasting models in three forecasting horizons. We noticed that the multivariate LSTM model outperformed the univariate one. The error from the multivariate model slowly grew when the forecast horizon was increased. However, the univariate errors rapidly grew with the increase in the forecast horizon.

5 Conclusion and Perspective

In this study, two LSTM models were tested to forecast the vehicle speed. The accuracy of the multivariate and univariate models was presented. The simulation

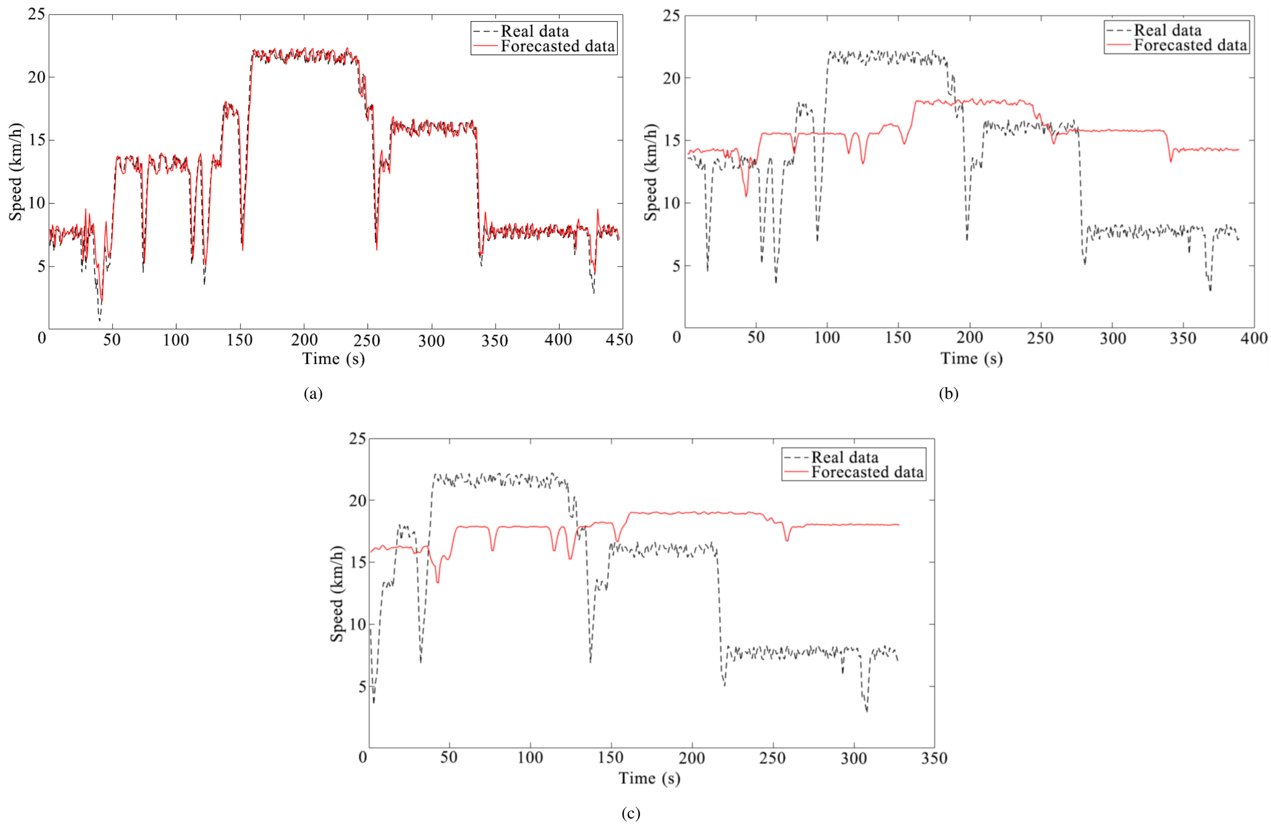


Fig. 3 EV speed forecasting results for the univariate LSTM model, (a) one step, (b) 60 steps, and (c) 120 steps.

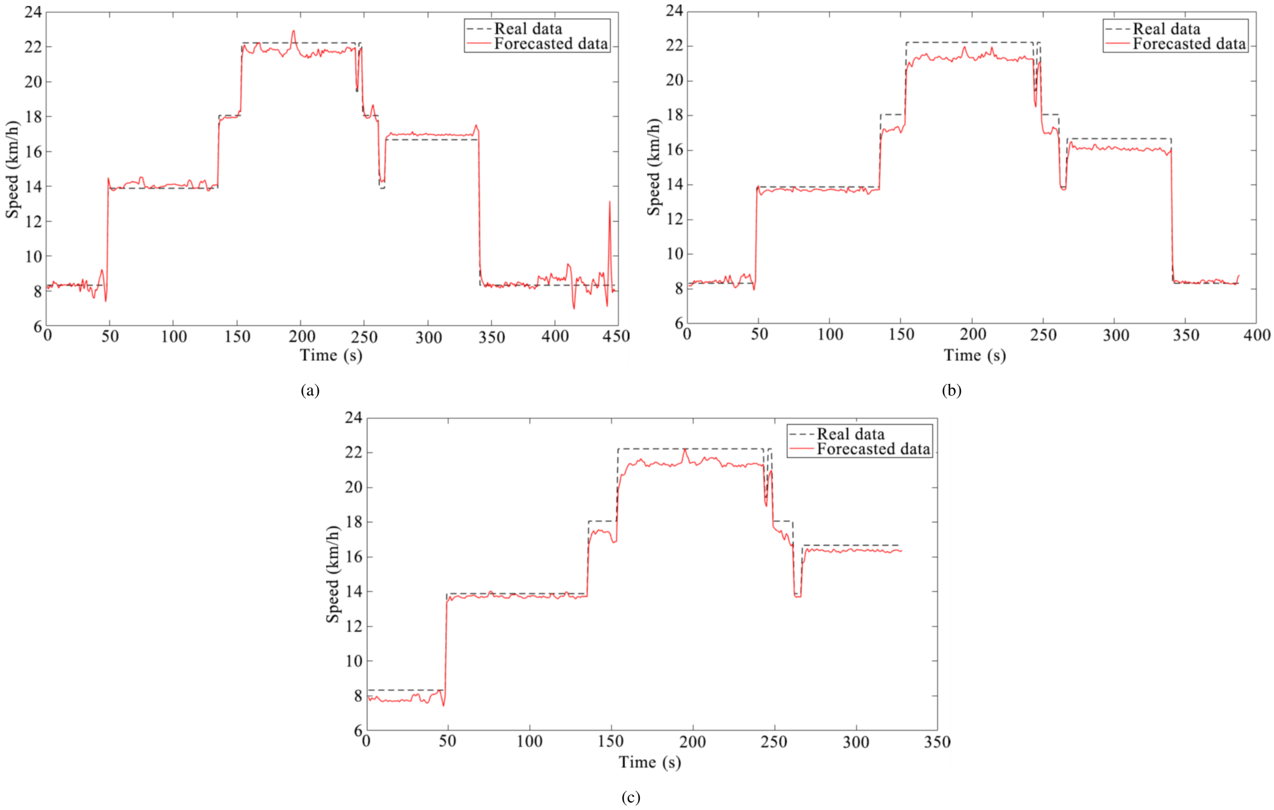


Fig. 4 EV speed forecasting results for the multivariate LSTM model, (a) one step, (b) 60 steps, and (c) 120 steps.

Table 1 RMSE error.

(%)

Training type	Forecast horizon		
	1 step	60 steps	120 steps
Multivariate	0.454	0.615	0.633
Univariate	1.033	5.427	7.184

Table 2 SMAPE error.

(%)

Training type	Forecast horizon		
	1 step	60 steps	120 steps
Multivariate	1.22	1.45	1.63
Univariate	3.94	17.14	21.68

results show that the multivariate model outperforms the univariate model due to the fluctuation of the speed with highly nonlinear factors, which are included in the used dataset for the multivariate model specification. As a perspective, we expect the deployment of the multivariate LSTM algorithm in a real test scenario that considers driver' s behavior and weather conditions. Pretrained forecasting models will be deployed in our EV platform for conducting experiments in real-sitting scenarios. The LSTM algorithm will be then tested in terms of efficiency (i.e., execution time) and accuracy.

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