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# Capturing Drivers' Lane Changing Behaviors on Operational Level by Data Driven Methods

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**ABSTRACT** With the development of autonomous vehicles, advanced driver-assistance systems, and vehicular social networks, the requirement for vehicle trajectory prediction in lane changing is higher. Here, we propose a neural-network-based operational level lane-changing model using data-driven methods. First, we determine the inputs of the lane-changing model by analyzing the influence factors of the lane-changing behavioral model under the framework of the social force theory. The main influencing factors include the temporal destination, the historical trajectories of the lane-changing vehicle, and the relative distance between the surrounding vehicles in our lane-changing model. Our lane-changing model is built by deep neural networks (DNNs). Then, we determine the suitable network structure and other parameters by empirical data for the DNN. Finally, tests on empirical lane-changing trajectory data sets show that the operational level lane-changing model built by DNN is promising.

**INDEX TERMS** Lane change, simulation, deep learning, neural network, recurrent neural network (RNN), social force, vehicular social networks (VSN).

## I. INTRODUCTION

Similar to car-following (CF), lane-changing (LC) is one of the primary driving tasks in traffic flow [1]. The LC rules describe vehicular lateral interactions on the road and thus play an important role in traffic flow theories [1]. Actually, LC behavior involves two different levels of behaviors. One is tactical-level behavior involving judgements and decisions, that is, lane-changing decision (LCD) behavior [2]. The LC behaviors on this level are more focused on the drivers' decision process on conflicting goals. The other is the operational level behaviors involving operating the vehicle after the lane-changing decision. LC behaviors on this level are the specific operations of the vehicles according to the situation of the surrounding vehicles during the execution of the LC. The mechanisms of these two levels of behaviors are quite different [3], [4].

With the autonomous vehicles (AV), advanced driver assistance systems (ADAS), the Internet of vehicles (IOV) and vehicular social networks (VSN) continue to evolve; there is a higher requirement for the accuracy of the vehicle's trajectory prediction [5]–[8], especially the vehicle's trajectory prediction in LC, due to the increasing evidence of LC's negative impacts on traffic safety [9], [10].

With the recognition of LC's significant impacts on traffic safety and congestion, efforts on LC modeling have rapidly increased over the last decade [1]. Although the conventional LC simulation model has made some achievements, researchers believe that there is still a lack of a traffic modeling tool that fully describes LC behaviors [1].

Most existing LC models (including conventional Gipps-type, cellular automata-based, or utility theory-based and Markov process-based models) are simplified for some reasons [1]. This inevitably lowers the flexibility and accuracy of the model, as some of the possible influencing factors are not considered in the simplified models, such as the car-following model [11].

With the development of data-driven technologies [11]–[14], it is natural to explore whether *it is possible* *to develop an LC model from empirical data by data-driven technologies.*Some scholars have attempted to apply neural networks (NNs), fuzzy neural networks and deep neural networks (DNNs) to predict drivers' LC decisions on the tactical level [15]–[19].

These early attempts applied NNs to predict the attempt of an LC for application in the ADAS, not the behaviors and decision-making process [15]–[19]. Thus, these models are not suitable for implementing in microscopic traffic flow simulations.

Third, most existing LC models process the immediate states of the subject vehicle and the adjacent influencing vehicles only [20]. They do not incorporate drivers' historical experience or predictive capacity into the model. How to make a suitable model structure to represent the time-dependent memory effect in the LC model is one of the key issues in our modeling.

Therefore, we propose a DNN-based LC model on the operational level from empirical trajectory data.

Our LC model takes the vehicular time-dependent dynamic states (velocities, positions, velocity differences, and position differences to surrounding vehicles, etc.) as time series data. These dynamic state-time series together with the LC type, vehicle type, and drivers' expected velocity are inputs of the model. The model output is the estimated velocity vector (with a direction and magnitude) of the target vehicle in the next time interval. The adopted input-output structure has some benefits. First, the whole model could be trained by empirical trajectory data, extracted from video data or other detected data sources. Second, the driver's historical experience or the prediction capability can be handled in the DNN. By regarding the vehicular dynamic states as time series data, the model is capable of capturing the historical data or the prediction capability during the LC period.

Here, we use empirical trajectory records extracted from the NGSIM dataset to train and test the DNN-based operational level LC model. The results of the model tests show that at the operational level, our LC model is more accurate than the commercial simulation model. Our study provides inspiration for capturing drivers' LC behaviors on the operational level and for new traffic simulation modeling.

The paper structure is as follows. Section II first analyzes the influencing factors of LC behaviors on the operational level and then presents the details of the DNN-based LC model. Section III presents the parameter settings and training of these DNNs by empirical trajectory data extracted from the NGSIM dataset. Section IV reports the LC model numerical testing results of the LC models. Section V discusses the results and provides conclusions.

## II. DNN BASED LC MODELS

To explore the effect of the NN-based LC model, we propose a feedforward neural network (FNN) LC model and gated recurrent unit (GRU) neural network-based LC model and perform a comparative analysis. The inputs/outputs of these two models are the same, while the structures of the hidden layer are different. By comparative analysis, we can better understand whether the traditional FNN is suitable for LC modeling. Fig. 1 shows our main work in NN-based LC modeling.

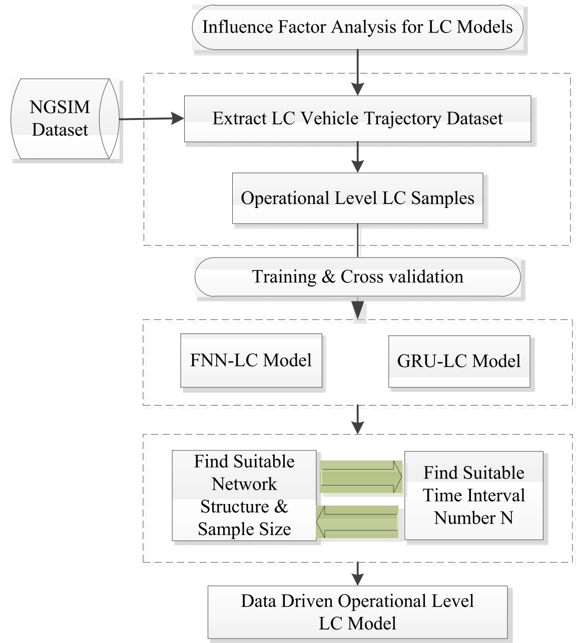



**FIGURE 1. Main work of DNN-based LC modeling.**

First, we analyze the influencing factors impacting the LC model to determine the inputs of the LC models. Then, we determine the input and output layers of the two NN models. Next, according to the input and output, the lane change-related data in the NGSIM database are extracted, and the operational level LC samples are constructed. We build the FNN and GRU neural networks for LC models. Then, by training and cross-validating the samples, we find the suitable network structures and sample size for the FNN and GRU networks for the LC models, respectively. Based on the suitable network structures and sample size, we also find the suitable historic time interval N by training and cross-validation. Then, we validate the suitable network structures and sample size again. Using the iterative method, we finally determine the suitable DNN-based operational level LC model.

### A. INFLUENCING FACTORS ANALYSIS FOR THE LC MODELS

The complexity of the LC behavioral model mainly comes from the conflicting goals and numerous influencing factors. In traditional simulation models, LC behaviors are usually divided into "discretionary" or "mandatory" behaviors, as the behaviors and decision-making processes of these two types of LC behaviors are significantly different [1], [21]. However, [22] classifies LC behaviors into three types: free, cooperative and forced LCs. Therefore, although LC type is an influential factor, it is unsuitable for use as LC model input. This is because the classification of LC types is different, and

LC types need to be calibrated artificially, which does not meet the requirements of data-driven modeling.

In recent years, the application of social force (SF) theory in microscopic traffic flow simulation modeling has gradually extended from pedestrians to riding behavior models of bicycles and vehicles [3]. The core idea of the SF behavioral model is that the change in the individual behavior $B$ is caused by the interaction between the individual's characteristics $P$ and the external environmental factors $E$:

$$B = f(P, E) \tag{1}$$

where $B$ stands for the behaviors of the subject person, $P$ stands for the personal characteristics of the person, and $E$ stands for the environmental influencing factors.

In LC behaviors, the drivers' personal characteristics include age, driving experience, gender and occupation. Due to the limitations of our sample, such features are not considered in our models. Hence, we mainly focus on the environmental influencing factors $E$.

Among the external environmental influencing factors $E$, one very important factor is the planned temporal destination TD, which is the output in the driver's short-term path/trajectory planning model. TD usually includes the location and expected arrival time [5], [7].

In our LC behavioral model, we assume that the different types of LC behaviors ("discretionary", "mandatory" or other types) are the results of the interactions of the LC vehicle (motivated by TD) with the surrounding vehicles. The LC type is an external phenomenon rather than an internal cause of LC behavior.

Therefore, when considering the model input, the type of the LC model is not taken as an influencing factor, but the vehicle temporal destination TD (including the expected time to reach the destination) as input of the LC mode is:

$$\overrightarrow{TD}_i\,(\mathrm{t}) = \{\Delta\overrightarrow{TD}_i\,(\mathrm{t})\,,\,\Delta T_{Di}\} \tag{2}$$

where $\Delta\overrightarrow{TD}_i$ (t) stands for the relative distance of the temporal destination (TD) to vehicle i, $\Delta T_{Di}$ stands for the relative expected arrival time at the TD for vehicle i:

$$\Delta\overrightarrow{D}_i\,(\mathrm{t}) = \overrightarrow{D}_i\,(\mathrm{t}) - \vec{s}_i\,(\mathrm{t}) \tag{3}$$

$$\Delta T_{Di} = T_{Di} - \mathrm{t} \tag{4}$$

where $\overrightarrow{D}_i$ (t) represents the position of the TD of vehicle $i$ at time $t$; $\vec{s}_i$ (t) is the trajectory of vehicle $i$ at time $t$; $T_{Di}$ represents the expected arrival time at TD of vehicle $i$.

Thus, our LC model combines easily with the path/trajectory planning model [5], [7] at the tactical level. The output of the LC path planning model —temporary destination TD — is the input of our operational LC model.

In addition to the TD of the planned path, the most direct influencing factor of LC behavior is the motion state of the LC vehicle and the relative dynamic states of the surrounding vehicles. In a typical process of an LC decision, the driver needs to choose the target lane and then search for an acceptable gap (usually defined as the headway gap between his/her

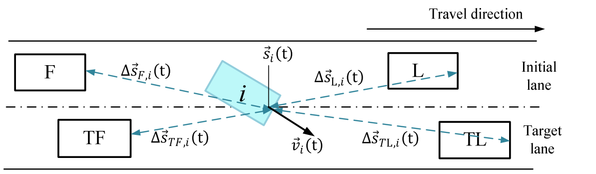



**FIGURE 2.** **Relative dynamic states of surrounding vehicles in a typical LC schematic.**

vehicle (the subject vehicle) and the leading vehicle and following vehicle in the target lane) and then to execute the change. During this process, the vehicle may still be in a car-following situation, so the leading car and following car in the initial lane may also influence the LC behavior. Therefore, the factors include the subject vehicle trajectory and velocity, the relative distances, directions and the relative velocities to other adjacent vehicles in the initial lane and target lane, as illustrated in Fig. 2. Here, "F" stands for the following vehicle, "L" for the leading vehicle, "TL" stands for the leading vehicle in the target lane, and "TF" stands for the following vehicle in the target lane.

To embody the direction and magnitude, the trajectory $\vec{s}_i$ (t) and velocity $\vec{v}_i$ (t) of the subject vehicle $i$are both vectors as follows:

$$\vec{s}_i\,(\mathrm{t}) = \{x_i\,(t)\,,\,y_i\,(t)\} \tag{5}$$

where $x_i(t)$ and $y_i(t)$ stand for the position of $i$ at the $x$ and $y$ axes at time $t$, respectively.

Similarly, the relative distance to the leading and following vehicles in the initial lane and target lane are all vectors, and if there is no surrounding vehicle j, the relative distance is set as infinity:

$$\Delta\vec{s}_{j,i}\,(\mathrm{t}) = \begin{cases} \vec{s}_j\,(\mathrm{t}) - \vec{s}_i\,(\mathrm{t}) & \textit{if j exists} \\ \infty & \textit{else} \end{cases} \tag{6}$$

and

$$\vec{s}_j\,(\mathrm{t}) - \vec{s}_i\,(\mathrm{t}) = \{x_j\,(t) - x_i\,(t)\,,\,y_j\,(t) - y_i\,(t) \tag{7}$$

where $x_j(t)$, $y_j(t)$ stand for the position components of vehicle $j$ in $x$ and $y$ axes at time $t$, respectively. Vehicle $j$ usually includes the leading and following vehicles in the initial lane, denoted as L and F, and the leading and following vehicles in the target lane denoted as TL and TF in the subscripts.

The velocity and relative velocity vectors can be derived directly from the position vectors:

$$\vec{v}_i\,(\mathrm{t}) = \Delta\vec{s}_i\,(\mathrm{t})/\tau = (\vec{s}_i\,(\mathrm{t}) - \vec{s}_i\,(\mathrm{t}-\tau))/\tau \tag{8}$$

and

$$\begin{aligned} \Delta\vec{v}_{j,i}\,(\mathrm{t}) &= \vec{v}_j\,(\mathrm{t}) - \vec{v}_i\,(\mathrm{t}) \\ &= \Delta\vec{s}_j\,(\mathrm{t})/\tau - \Delta\vec{s}_i\,(\mathrm{t})/\tau \\ &= \frac{\vec{s}_j\,(\mathrm{t}) - \vec{s}_j\,(\mathrm{t}-\mathrm{T})}{\tau} - \frac{\vec{s}_i\,(\mathrm{t}) - \vec{s}_i\,(\mathrm{t}-\mathrm{T})}{\tau} \end{aligned} \tag{9}$$

where $\overrightarrow{v}_i$ (t) stands for the velocity components of $i$ at time $t$, $\Delta\vec{s}_i(\mathrm{t})/\tau$ for the moving trajectory of $i$ from time $t$-$\tau$to$t$. When the time step $\tau$is small enough, $\Delta\vec{s}_i(\mathrm{t})/\tau$ can represent the instantaneous speed of vehicle $i$ at time $t$.

Then, by (8) and (9), all the velocity-related variables can be calculated from the previous and current trajectory data. Considering the powerful learning and calculation functions of the DNN models, the velocity data can be omitted without any information loss when the historical trajectory data are also put into the model.

Moreover, regarding the drivers' historical experience or the prediction capability in the LC models, we also take the vehicles' previous trajectory data a few seconds before.

Thus, the inputs of the social force-based operational level LC models are as follows:

$$\begin{aligned}\mathrm{Input} = \{&\overrightarrow{TD}_i(\mathrm{t});\mathrm{L}_i;\vec{s}_i(\mathrm{t}-\tau);\mathrm{L}_j;\Delta\vec{s}_{j,i}(\mathrm{t}-\tau);\\ &\vec{s}_i(\mathrm{t}-2\tau);\Delta\vec{s}_{j,i}(\mathrm{t}-2\tau);\ldots\ldots\\ &\vec{s}_i(\mathrm{t}-\mathrm{N}\tau);\Delta\vec{s}_{j,i}(\mathrm{t}-\mathrm{N}\tau);\}\\ &\mathrm{j}=\mathrm{L, F, TL\ and\ TF}\end{aligned}\tag{10}$$

where Input stands for the inputs of the operational level LC model; $L_i$ and $L_j$ stand for the vehicle length of vehicles $i$ *and j*, which is often closely related to the types of vehicles. The types of vehicles often include motorcycles, auto cars and trucks, so we took the vehicle length to represent the influence of the vehicle type. $\tau$ is the time step to the calculated velocity, considering the current development of vehicular social networks (VSN) and IOV data acquisition technologies, as well as speed data accuracy requirements, $\tau$=0.2 $s$. $T$ stands for the time interval of the model. Referring to the previous study on modeling car-following by DNN [11], we set $T$=1 s. N stands for the parameter defining the length of the influencing previous time interval NT, and we will discuss this parameter in section IV.

### B. FNN BASED LC MODEL

Based on the above analysis of the influence factors of the operational level LC model, we propose a feedforward neural network (FNN) LC model, which is formulated as follows:

$$\begin{cases}\widehat{\Delta\vec{s}}_i(\mathrm{t}|\theta) = f\begin{pmatrix}\overrightarrow{TD}_i(\mathrm{t});\mathrm{L}_i;\vec{s}_i(\mathrm{t}-\tau);\Delta\vec{s}_{j,i}(\mathrm{t}-\tau);\\ \ldots\ldots\\ \vec{s}_i(\mathrm{t}-\mathrm{N}\tau);\Delta\vec{s}_{j,i}(\mathrm{t}-\mathrm{N}\tau);\end{pmatrix}\\ \hat{\vec{s}}_i(\mathrm{t}|\theta) = \vec{s}_i(\mathrm{t}-\mathrm{T}) + \widehat{\Delta\vec{s}}_i(\mathrm{t}|\theta)\end{cases}$$
$$\mathrm{j}=\mathrm{L, F, TL\ and\ TF}\tag{11}$$

where $\widehat{\Delta\vec{s}}_i(\mathrm{t}|\theta)$ is the estimated moving distance of the LC vehicle $i$ from ($t$-$T$) to $t$, $\hat{\vec{s}}_i(\mathrm{t}|\theta)$ is the estimated trajectory of the LC vehicle $i$ at $t$.

Both LC functions $f(\bullet)$ are learned by neural networks. $\theta$ are the parameters of the NN, mainly including the weight vector and transfer function. Other notations are the same as (9).

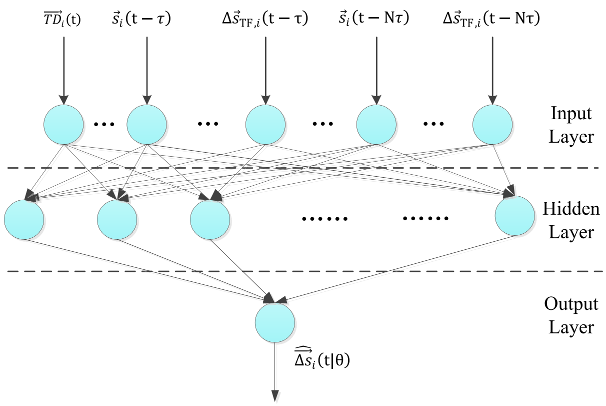



**FIGURE 3. The structure of FNN for LC models.**

Fig. 3 presents the structure of the FNN-based LC model. The structure contains three types of layers. The neurons of the input layer take the inputs, while the neurons of the output layer generate the outputs [17]. This FNN model contains one or more hidden layers, which contain a number of neurons.

Here, we take the sigmoid function as a transfer function for neurons, which has been widely used and proven to be suitable for the car-following model [11].

According to the data-driven modeling theory, if the sample size and quality are high enough, the samples reflect all the mechanisms of drivers' LC behaviors. The structure of the neural network is very powerful, which means it can learn all the mechanisms of drivers' LC behaviors. Therefore, we believe that such an NN-based LC model can represent the drivers' LC behaviors properly.

### C. GATED RECURRENT UNIT (GRU) NEURAL NETWORK BASED LC MODELS

To better capture the drivers' LC behavior features, we apply more powerful neural networks to operational level LC models, which is also formulated as (10).

Scholars have proposed a number of NNs to perform deep learning. Here, we implement the gated recurrent unit (GRU) neural network, which is a kind of recurrent neural network (RNN) [23]–[25]. The structure of GRU networks for the LC model is shown in Fig. 4. In RNNs, the connections of the neurons of the hidden layer can form a directed cycle. The directed cycles create an internal state of the network, making it possible to exhibit dynamic temporal behavior, such as the memory effect of the human brain.

In Fig. 3, we can see that all inputs of FNN are independent of each other. Different from FNN, RNNs can process any sequence of input with their internal states. For the length of the paper, neuron output functions are not presented here. Interested readers can refer to [11] and [24].

The primary purpose of applying deep learning methods to operational level LC modeling is to enhance the learning capacity of NNs. In theory, with proper transfer functions and neuronal quantities of the hidden layers, a three-layered NN also has the power to capture any behavior rules,

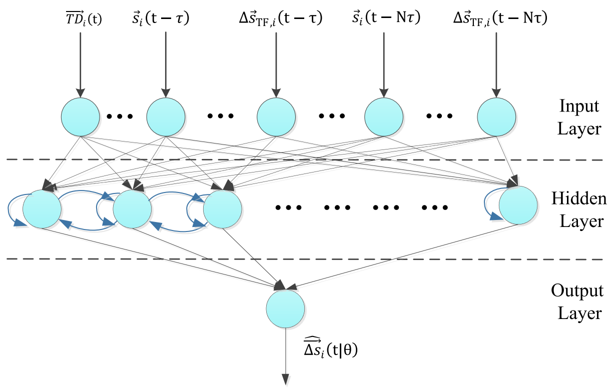



**FIGURE 4.** The structure of FNN for LC models.

including LC. However, multilayer neural network models (also called deep learning) have obtained state-of-the-art achievements in many challenging tasks, including computer vision, natural language processing, speech recognition, handwriting recognition, and traffic flow forecasting [26]–[29].

## III. NEURAL NETWORK TRAINING FOR LC MODELS

The training of NNs can be regarded as the process of minimizing the error between model outputs and samples. This section contains three parts: performance index, decision variables and training algorithms of neural networks.

According to [30]–[32], we adopt the widely used mean squared error (MSE) of empirical and estimated trajectories as a performance index. For further information on the MSE formula, interested readers can refer to [3], [11], and [30]–[32].

There are four types of decisive parameters in our DNN-based operational level LC models.

### A. TIME INTERVAL NUMBER N OF MODEL INPUTS

Here, the value of N represents the amount of vehicle history trajectory information being input into the neural networks. The larger N means more historical trajectory information is put into the neural networks.

To validate the best value of time interval number N, we trained different neural networks with different N, from 2 to 9, and tested them with the LC sample database. Model tests show that N=5 of historical input might be a reasonable choice. Test results are presented in section IV.

### B. TRANSFER FUNCTION

According to [11], the sigmoid function is chosen as the transfer function for neurons in the input/output layers of the FNN and GRU neural networks.

For neurons in the hidden layers, the sigmoid function and ReLU function [24], [25] are chosen as the transfer functions for the FNN and GRU models, respectively. The ReLU function is as follows:

$$g_{ReLu} = max\,\{1, z\} \tag{12}$$

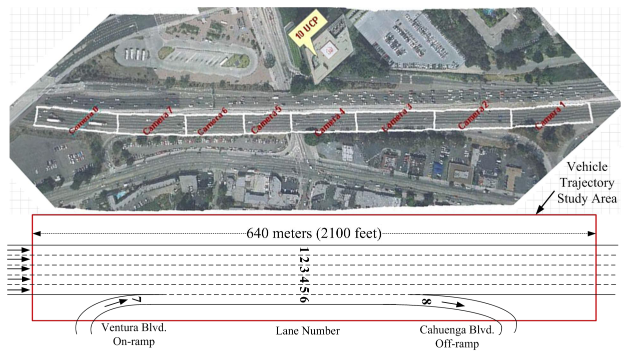



**FIGURE 5.** The study area in the NGSIM U.S. Highway 101 dataset.

### C. THE STRUCTURE OF NNS

The structure of neural networks includes the number of hidden layers and neurons in them.

There is no explicit method to determine the most suitable structure of neural networks. We can only obtain a suitable NN structure by empirical data testing. We have trained and tested several representative NN structures and found that the structure is highly correlated with the training sample size. The test results are presented in Section IV.

Corresponding with recent work [11], we apply the back-propagation (BP) algorithm [33] to train the FNN-based LC models and the stochastic gradient descent algorithm [34] to train the GRU-based LC models.

Later, the cross-validation method is applied to solve the problem of underfitting and overfitting of NN-based models. Thus, we can judge that our DNN-based models are under-trained, overtrained or trained properly.

Section IV presents the results of model cross-validation.

## IV. TESTING RESULTS

In this section, we will perform tests on our LC models using empirical data. First, we introduce the testing empirical data. Then, we compare different structures of the FNN- and GRU NN-based LC models together with different training sample sizes. Next, based on the appropriate training sample sizes and structure, we determine the time interval number N. Last, we compare the performance of the FLOWSIM-LC model and our DNN-based LC models.

### A. TESTING DATA

The next generation simulation (NGSIM) is chosen as our testing dataset because it provides reliable and accurate trajectory data and other related information (such as the initial lane, target lane, leading vehicle ID, and following vehicle ID), which is ideal for operational level LC behavior modeling. The dataset is of U.S. Highway 101. The study area is approximately 640 meters long, with one on-ramp and one off-ramp. The vehicle trajectory study area and the lane numbers are shown in Fig. 5.

In sample data preprocessing, we separated successive LC movements executed by one vehicle into different single LC cases. For example, LC 4-5-6 (meaning that the vehicle

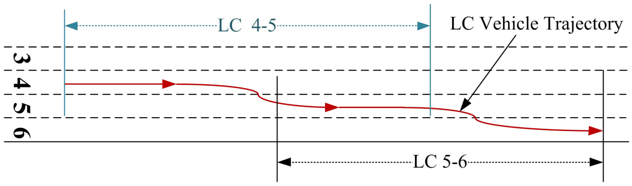



**FIGURE 6.** Schematic of separating successive LC movements into single LC cases.

moves from lane 4 to lane 5 and then to lane 6, as shown in Fig. 6), we separated the successive LC cases into two different LC cases: LC 4-5 and LC 5-6. To obtain as many data samples as possible, we put all the suitable data of the lane change case into a single lane change sample.

After preprocessing, we obtained 1378 LC cases and 146,435 records of LC vehicle trajectories for training/testing. We obtained over 141,127 valid sample records. The LC samples extracted from the NGSIM dataset are denoted as empirical LC data.

### B. FINDING THE SUITABLE MODEL STRUCTURE AND SAMPLE SIZE

To implement DNN to a relatively small dataset, we should be cautious about overfitting and underfitting. As complicated, NN is prone to overfitting with a small sample size.

According to [36], the overfitting problem in training NN is more serious. When the model is overfitting, although the error of the model on the training dataset is very small, the error on the testing dataset becomes large. To avoid this mistake, we test different network structures from simple to complicated structures.

Because it is difficult to determine the correlation of the training sample size and the neural network structures [11], we test different schemes (see Table 1) to find suitable neural network structures.

We randomly divided the entire empirical LC sample into three parts: 40% as the training dataset, 30% as the cross-validation sample, and the remaining 30% as the test dataset.

For all the neural network schemes in Table 1, generally at least 10,000 to 50,000 samples (8% to 35% of the total sample) are required. The test results show that most of the weight coefficients of the models do not approximate 0, which shows that the proposed NN models work with efficiency by the cross-validation method.

Figs. 7 and 8 show the MSE values in feet$^2$ of the FNN model and GRU neural network-based LC models in different training samples and structure schemes, respectively. Here, the time interval number N of the model input is taken as 5.

The results show that the GRU neural network LC model with structure scheme 7 in Table 1, trained by 30,000 samples, obtained the best performance. The FNN LC model with structure scheme 3 in Table 1, trained by 25,000 samples, obtained the best performance.

We chose the neural network structure with the best performance as our LC model structure and called it the FNN-LC model (structure scheme 3, N=5) and GRU-LC model (structure scheme 7, N=6).

The results on the NN structures indicate that DNNs are better than shallow NNs in modeling LC behaviors on the operational level.

**TABLE 1.** NN structure schemes tested.

| Structure Schemes | Hidden Layer 1 | 2 | 3 |
|---|---|---|---|
| S 1 | 30 | -- | -- |
| S 2 | 50 | -- | -- |
| S 3 | 100 | -- | -- |
| S 4 | 200 | -- | -- |
| S 5 | 300 | -- | -- |
| S 6 | 10 | 10 | -- |
| S 7 | 30 | 30 | -- |
| S 8 | 50 | 50 | -- |
| S 9 | 70 | 70 | -- |
| S 10 | 10 | 10 | 10 |
| S 11 | 30 | 30 | 30 |
| S 12 | 50 | 50 | 50 |

Notes: -- denotes the structure schemes that do not have the corresponding layer.


**FIGURE 7.** MSE in feet$^2$ of FNN with different structure schemes and training sample sizes (N=5).

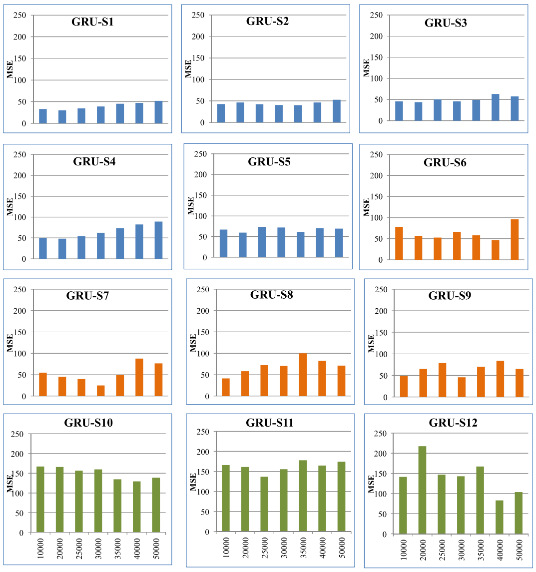



**FIGURE 8.** MSE in feet$^2$ of GRU neural networks with different structure schemes and training sample sizes (N=6).

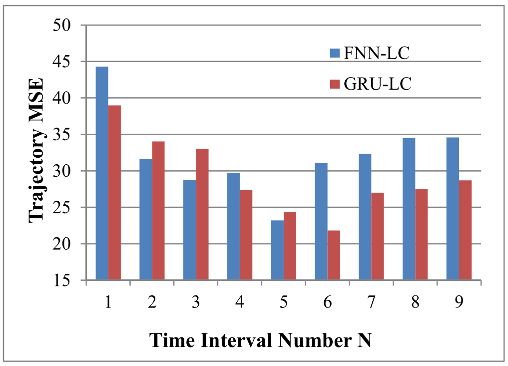



**FIGURE 9.** MSE in feet$^2$ of FNN- LC and GRU-LC models with different time interval numbers N.

### C. THE APPROPRIATE VALUE OF TIME INTERVAL NUMBER N

Before finding the best structures of the FNN and GRU LC model, we selected 10,000 training samples to test and compare different Ns. The preliminary results show that N=5 or 6 are appropriate choices.

Then, we chose N=5 to test and compare the different network structure schemes and training sample sizes and obtain the optimal structure schemes and the corresponding training sample sizes for the FNN-LC model and the GRU-LC model, respectively (details see section IV-B).

Next, with the best network structures and corresponding training sample sizes, we tested the FNN-LC model and the GRU-LC model with different N values, and the results are shown in Fig. 9. The results show that N=5 for FNN-LC and N=6 for GRU-LC achieve the best performance.

### D. COMPARISON OF TRAJECTORY PREDICTION ACCURACY

To examine the trajectory prediction accuracy of our LC models, we compared the distributions of trajectory deviations of the FNN-LC model, the GRU-LC model and the FLOWSIM-LC model in the test LC dataset.

The FLOWSIM-LC model is the LC model in the commercial microscopic traffic flow simulation model—FLOWSIM 2.1 version. The vehicles' car-following and LC behavioral model of FlowSIM 2.1v are both based on fuzzy logic [37]–[39].

The test dataset was randomly extracted from the NGSIM empirical LC test dataset.

According to the statistical facts of the samples from the NGSIM dataset, the parameters of this FlowSIM simulation model were set as [11].

Fig. 10 compares the distributions of MSE on the trajectory of LC vehicles of the FNN-LC Model, the GRU-LC Model and the FlowSIM-LC models.

Fig. 10 shows that the GRU-LC model is more accurate than the other models in trajectory prediction of the subject vehicles in LC situations.

To give an illustration of the spacing estimation errors, we randomly selected one "Mandatory" and one "Nonmandatory" LC case in the US 101 dataset. Here, we set all LC cases for vehicles that finally exited via lane 8 as "Mandatory" and for vehicles entering from the on-ramp (i.e., lane 7) and then changing from lane 6 to lane 5 as "Mandatory" (this case should be viewed as a "Mandatory" case as if the vehicle had not changed lanes, it would soon exit via lane 8 in 150 m). Other LC cases were set as "Nonmandatory" cases.

In the "Mandatory" LC case, the ID of the LC vehicle is 4 changes from lane 6 to 5, without the leading vehicle or target lane leading vehicle, the ID of the following vehicle is 6,

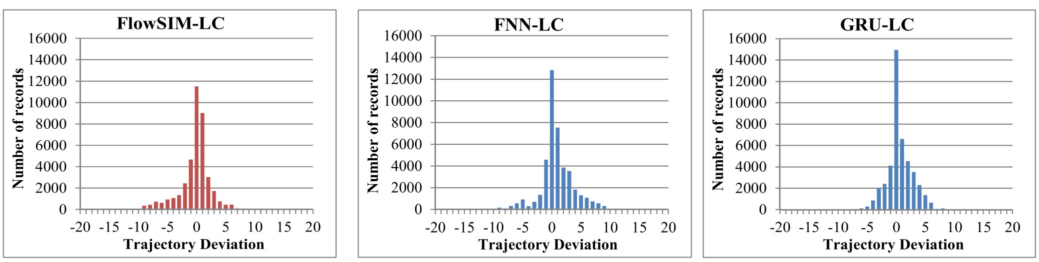
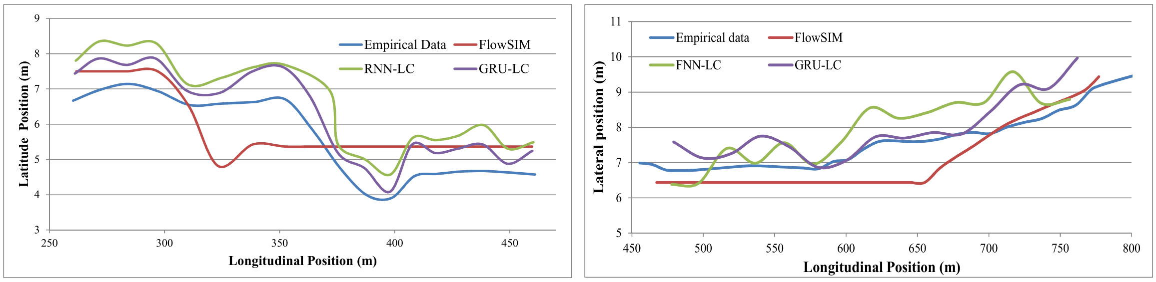



**FIGURE 10.** Distributions of trajectory deviations of three models in all LC situations.




(a) (b)

**FIGURE 11. The LC vehicle trajectory replicated by different models in "Mandatory" and "Nonmandatory" LC situations. (a) "Mandatory" LC situation. (b) "Nonmandatory" LC situation.**

and the ID of the target lane following vehicle is 14. In the "Nonmandatory" LC case, the ID of the LC vehicle is 233, changing from lane 5 to 4. The ID of the leading vehicle, the following vehicle, the target lane leading vehicle and the following vehicle are 231, 246, 228 and 245, respectively. Fig. 11 shows the LC vehicle trajectory replicated by different models.

## V. DISCUSSIONS & CONCLUSIONS

Like all data-driven models, the quality and quantity of training samples determine the performance of the FNN and GRU neural network-based LC models.

First, the relative distance and relative speed of our vehicle and the surrounding vehicles were used as inputs to the model. However, in the actual operation, the velocity must be in the form of a vector in LC samples. The speed data of the original NGSIM do not contain this information. We tried to use the trajectory information to calculate the velocity vector, but the result was not ideal, as many speeds exceeded the actual speed range. Therefore, the results of the training were not satisfactory.

Then, we input the immediate and historical trajectory information and relative distance simultaneously, instead of the original trajectory, relative distance, velocity, and relative velocity input. The results of training were satisfactory this time, as the quality of the sample was guaranteed.

However, this also indicates that our FNN-LC and GRU-LC models trained by the limited samples in the NGSIM dataset cannot meet the simulation requirements of all situations. However, our main contribution of the work is attempting to apply social force (SF) behavior theory and data-driven modeling to more complex driving behaviors, such as operational level LC behavior modeling.

In addition to providing a basic model framework and methodology for building localized online simulation models, the NN-based operational level LC model can also be applied to intelligent vehicle research, as in the advance driving assistant system (ADAS). The LC model can be applied to predict the trajectory of the front adjacent lane vehicle in an LC case and provide basic information for further safety judgement and strategy. Another promising use is to apply an NN-based LC model to estimate the surrounding human-driven vehicles in virtual tests of ADAS in intelligent vehicles or AVs [5].

In this paper, we attempt to build an NN-based operational level LC model using pure vehicle trajectory data. Empirical data tests showed that the new NN-based operational level LC model was more accurate in trajectory prediction than existing LC models of commercial simulation software.

The research results may be part of the response to the question proposed by [11]: "Whether is it possible and whether is it necessary to build a new traffic simulation software in a pure deep learning way?".

Our test results show that with the proper model input/output from the theoretical framework support, we can build a relatively simple NN structure with a medium sample size with satisfactory results. For instance, in this paper, the three-layered FNN model with 100 neurons in the hidden layer, trained by a 25,000 sample, we can obtain satisfactory results. However, the performance of the more complex GRU-LC model generally performs better than FNN.

Therefore, we believe that with the support of a proper theoretical framework (such as the social force behavioral model framework), we can make better use of data-driven modeling methods. We can build simulation models using a simple NN structure with a medium training sample size and obtain satisfactory simulation results as well. In addition, this research can provide a useful reference to many research fields about future vehicles and transportation, both of which are used in future energy and smart cities [40]–[44].

The lane change is a series of complicated behaviors containing tactical and operational levels of behaviors. Therefore, a more appropriate approach may be to build the two different levels of LC behavior models (tactical and operational level) separately. Our future work will attempt to build LC models that incorporate these two levels of LC behaviors.

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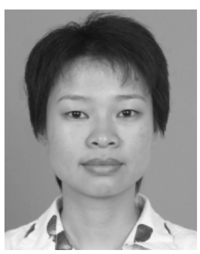

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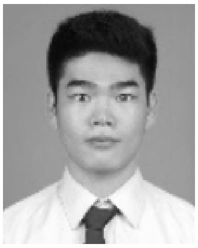

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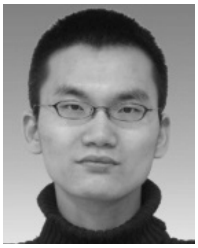

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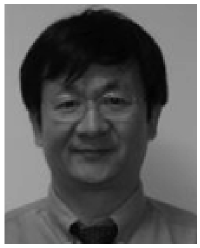

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