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Traffic Speed Prediction under Weekday Using Convolutional Neural Networks Concepts

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Abstract— **For providing drivers with robust traffic information and Optimizing the energy management of Hybrid Electric Vehicles (HEVs), it is important to predict traffic information accurately with past traffic information. As acquisition of the traffic information have been easier by the development of Intelligent Transportation System (ITS), active study on traffic prediction is currently underway. Multi-Layer Perceptron (MLP) model have been widely utilized for predicting traffic information since it is appropriate to represent the non-linear characteristics inherent in traffic prediction. However, the MLP model doesn't reflect local dependencies of traffic data and is prone to noise in traffic data. Convolutional Neural Networks (CNN) based model, on the other hand, can capture the local dependencies of traffic data and is less prone to disturbance in data. In this paper, we use temporal data and speed data collected on main roads in Seoul, South Korea to construct traffic prediction models. The speed data which are collected by every 5 minutes are provided by Ministry of Land, Infrastructure and Transport in South Korea. We construct the CNN based model and two MLP models which predict traffic speed and compare performance of the prediction models in this paper. The comparison results show that the CNN based model's prediction performance is higher than the prediction performance of the other two MLP models.**

I. Introduction

Forecasting traffic information precisely is important in various aspects. The accurate forecasting of traffic is essential element to provide robust traffic data to drivers, control the traffic, and plan the public transportation systems. Also, it is possible to develop the optimal power management strategy of hybrid electric vehicles, if the traffic information is predicted precisely [1]-[3]. Due to this importance, many studies have been conducted to predict traffic information through past traffic information. Many traffic prediction models have been introduced, including Autoregressive Integrated Moving Average (ARIMA) model [4],[5], Multi-Layer Perceptron (MLP) model [6]-[9], and non-parametric regression model [10],[11]. Among them, MLP model has been considered as very powerful approach for forecasting traffic information because it is suitable for representing the complex non-linear characteristics which is inherent in traffic prediction. E. Lee et al. [7] constructed a MLP model predicting traffic speed on main roads in Seoul, South Korea by using temporal data and neighboring roads' speed. J. Park et al. [9] modeled several types of MLP models depending on days of the week, traffic congestion level, and prediction time intervals to predict traffic speed precisely.

Although past studies showed that a MLP model is suitable for predicting traffic, the MLP model has drawbacks that it can't capture local dependencies and is vulnerable to noise of data. Convolutional Neural Networks (CNN) based model, on the other hand, has advantages that it can capture the local dependencies and is less sensitive to noise in data [12]-[13]. Due to these advantages of CNN, big advances have been made in many research fields including image recognition and activity recognition by using CNN based approaches [12]-[14].

In this paper, we construct two MLP traffic speed prediction models and a CNN based traffic speed prediction model by using temporal data and traffic speed data collected on main road in Seoul. The speed data are collected by every 5 minutes and provided by Ministry of Land, Infrastructure and Transportation in South Korea. After the three prediction models were built, the performance of the three models are compared by mean absolute error on test data. The comparison results show that the CNN based model outperform the two MLP models.

II. Data Description and Data Processing

Past traffic speed data collected on main road in Seoul and temporal data are used to forecast traffic speed. Fig. 1 shows the locations of four links on which traffic speed was collected. Link1000008004 extends from node1000012900 to node1000013100 and link1000008005 extends from node1000013100 to node1000015700. Also, link1000008006 extends from node1000015700 to node1000016300 and link1000008007 extends from node1000016300 to node1000016600. For convenience, we name link1000008004, link1000008005, link1000008006, and link1000008007 as link1, link2, link3, and link4 respectively.

In this paper, we build traffic speed prediction models which forecast traffic speed on link 3 shown in Fig. 1. We use five types of data which are collected in weekday to construct the traffic speed prediction models. One type of the data is temporal information about prediction time and the remaining

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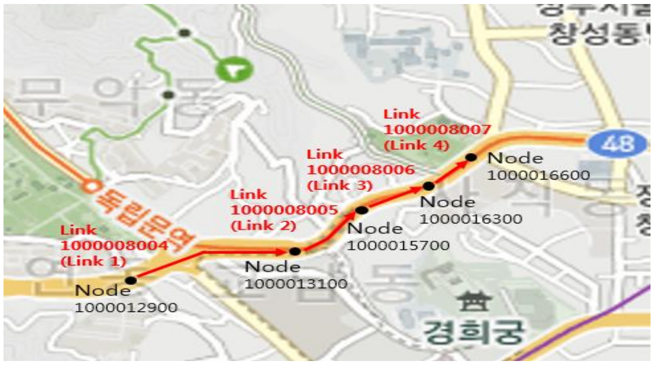


Figure 1. Map showing locations of node and link: map is provided by Daum

TABLE I. BINARIZATION PROCESS ABOUT THE DAY OF WEEKDAY

The day of Weekday	**Input nodes in input layer**				
	x_1	x_2	x_3	x_4	x_5
Monday	**1**	0	0	0	0
Tuesday	0	**1**	0	0	0
⋮	⋮				
Friday	0	0	0	0	**1**

TABLE II. BINARIZATION PROCESS ABOUT HOUR

Hour	**Input nodes in input layer**				
	x_6	x_7	…	x_{28}	x_{29}
00-Hour	**1**	0		0	0
01-Hour	0	**1**		0	0
⋮	⋮	⋮	…	⋮	⋮
23-Hour	0	0		**1**	0
24-Hour	0	0		0	**1**

TABLE III. BINARIZATION PROCESS ABOUT MINUTE

Minutes	**Input nodes in input layer**					
	x_{30}	x_{31}	x_{32}	x_{33}	x_{34}	x_{35}
from 00min to 10min	**1**	0	0	0	0	0
from 10min to 20min	0	**1**	0	0	0	0
⋮	⋮					
from 40min to 50min	0	0	0	0	**1**	0
from 50min to 60min	0	0	0	0	0	**1**

four types of data are past traffic speed profile collect on the four links.

It is essential to process the temporal data for constructing the MLP models and the CNN model. The temporal data have not ordinal characteristics, they are processed by binarization [7]. The temporal data contain information about the day of weekday, hour, and minute. Table I shows the specific binarization processing about the day of weekday. x_i shown in Table I to Table III denotes input of node in input layer of the prediction models where subscript i is an index for input nodes ($i \in \{1, 2, 3, \ldots, 35\}$). The size of the nodes about the day of weekday is 5 and each of the nodes is activated in 1 when a relevant weekday is input to the traffic speed prediction models. Table II shows the binarization processing about hour. The size of the nodes related to hour is 24 and each of the nodes is activated in 1 when a corresponding hour is entered to traffic prediction models. Table III represents the binarization processing about minute. The size of the nodes related to minute is 6 and each of the nodes is activated in 1 when a relevant minute band is input to prediction model.

Traffic speed profiles of the four links are utilized to construct the traffic speed prediction models. 5 traffic speed data on each of the links are used to forecast traffic speed on link3. Fig. 2 represents the traffic speed data of the each link utilized to forecast traffic speed. There are three main variables: $v(t)$, $v(t\text{-}k\Delta t)$, $v^T(t+i\Delta t)$. $v(t)$ denotes the traffic speed at the moment that future traffic speed is predicted. $v(t\text{-}k\triangle t)$, where $k\in\{1,2,3,4\}$ and $\Delta t=5min$ denotes traffic speed before the future traffic speed is predicted. The $v(t)$, and the $v(t\text{-}k\Delta t)$ of each link are used to forecast the future traffic speed. These speed data are normalized to have a value between 0 and 1 to reduce the deviation between temporal data and speed data. And $v^T(t+i\Delta t)$, where $i\in\{1,2,3,6\}$, represents future traffic speed at different prediction time intervals: 5 min, 10 min, 15 min, and 30min.

Traffic speed data collected on 7th, 8th, 9th, 13th and 20th day of January, 12th and 13th day of February, and 2nd, 24th, 25th and 26th day of March, 2015 are used for training the traffic speed prediction models. And Traffic speed data measured on 6th and 10th day of March, 2015 are used for testing the performance of the prediction models.

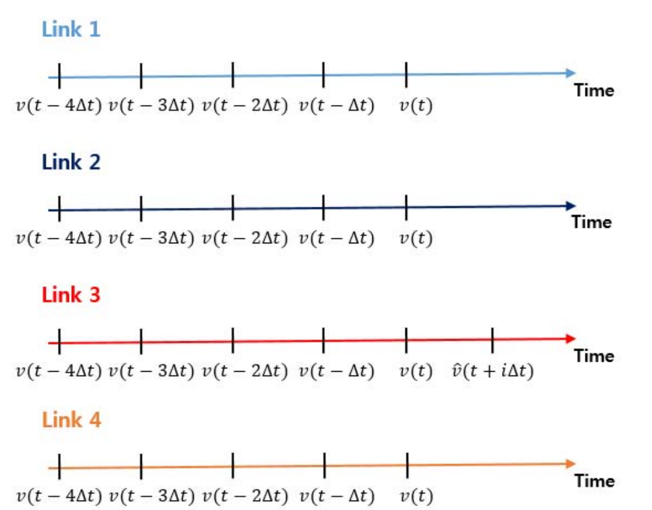


Figure 2. Illustration about traffic speed data on each of the links for speed prediction on link 3

III. Development of Traffic Speed Prediction Models

In this section, we will describe how the three traffic speed prediction models are designed. One of the three prediction models is CNN based prediction model, and the other two models are MLP prediction models whose architecture are totally different. One MLP model has only one input layer which takes temporal data and speed data on the four links all together. The other MLP model has five input layers which takes temporal data and four links' speed profiles separately.

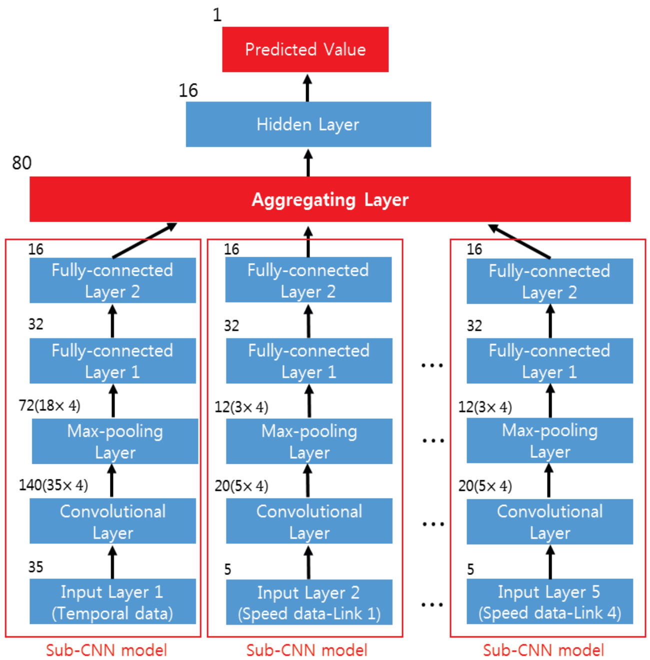


Figure 3. Architecture of CNN based prediction model

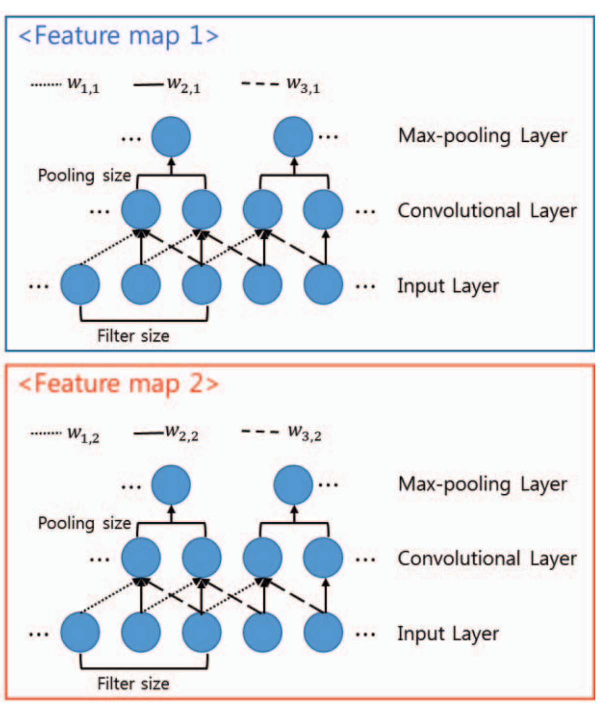


Figure 4. Illustration for convolutional layer

A. CNN based Traffic Speed Prediction Model

Architecture of the CNN based traffic speed prediction model is represented in Fig. 3. In Fig.3, numbers located in the corner of boxes indicate size of nodes in corresponding layers. There are five input layers in which different types of data are entered. One input layer takes temporal data and the other four input layers take speed profile of link 1, speed profile of link 2, speed profile of link 3, and speed profile of link 4, respectively. Therefore, the CNN model consists of five sub-CNN models. The number of output nodes in the sub-CNN model is 16. The output of the five sub-CNN models is concatenated in aggregating layer. Thus, the number of nodes in the aggregating layer is derived from product of the number of sub-CNN models and size of the output nodes in a sub-CNN model.

All the 5 sub-CNN model include convolutional layer and max-pooling layer and we use zero-padding to form the convolutional layer and max-pooling layer. There are multiple feature maps in convolutional layer. Since local filter which is used in convolution operation with local subset of nodes in the previous layer is different according to the feature map, it is essential for the CNN-based model to have multiple feature maps to increase flexibility of the model. Fig. 4 illustrates the structure of convolutional layer in our CNN based prediction model. $w_{i,j}$ expressed by different types of line in Fig.4 denotes weight that is element of the local filter. The subscript i is an index about location in local filter and the subscript j is an index representing different feature maps ($i \in \{1,2,3\}$, $j \in \{1,2,3,4\}$). The local filter can be represented in 1-dimensional vector [$w_{1,j}$, $w_{2,j}$, $w_{3,j}$] and is tuned by backpropagation algorithm.

For capturing the local dependencies and exploiting strong relationship in nearby data, nodes in convolutional layer are only connected to a fraction of nodes in previous layer [12]. In traffic speed profile on arbitrary links, the nearby speed data are likely to be correlated, and the CNN model can capture this local dependencies in the speed profile.

Output of node in the convolutional layer is derived by convolution operation of the local filter whose size is m and a subset nodes in input layer as follows:

$$h_{i,j} = \sigma\left(\sum_{a=1}^{m} w_{a,j} \cdot x_{i-1+a} + b_j\right) \qquad (1)$$

where, $h_{i,j}$ denotes output of i-th node in j-th feature map of convolutional layer, x_i represent a value of i-th node in input layer, b_j represents a bias for j-th feature map, and $\sigma(\cdot)$ is a activation function. In this paper, we use Rectified Linear Units (ReLU) as activation function. ReLU is expressed as follows:

$$\sigma(x) = \max(0, x) \qquad (2)$$

B. MLP Traffic Speed Prediction Models

We design two version of MLP prediction model which have a comparable parameter size with CNN-based model. An architecture about one of the two MLP models is shown in Fig. 5. This MLP model has only one input layer which takes

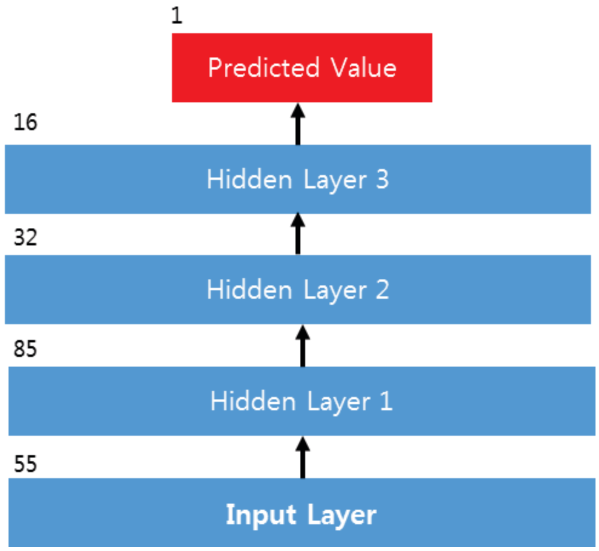


Figure 5. MLP prediction model which has only one input layer

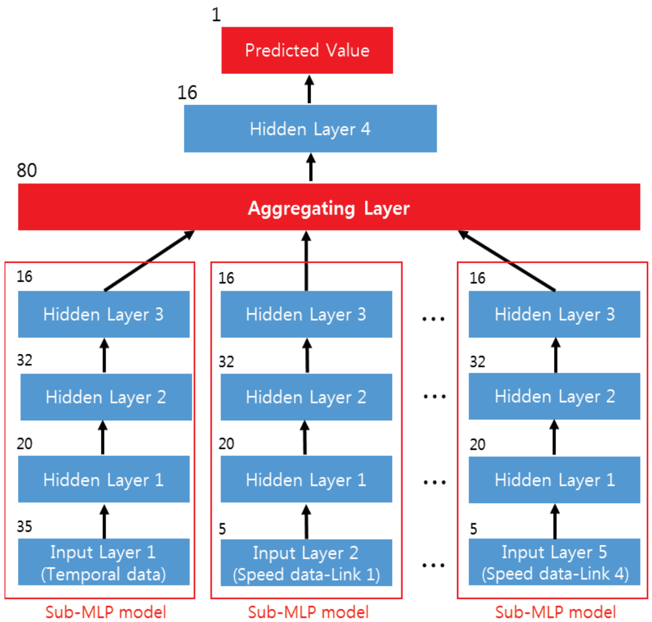


Figure 6. MLP prediction model which has five input layers

the temporal data and the speed profiles measured on the four links all together. Fig. 6, on the other hand, shows the other MLP model's architecture. The input layer of the MLP model illustrated in Fig. 6 is same with input layer of the CNN-based model. One input layer takes temporal data and the other four input layers take the speed profile on link 1, the speed profile on link 2, the speed profile on link 3, and the speed profile on link 4, respectively. Therefore, this MLP model is composed of five sub-MLP models and output of the five sub-MLP models is concatenated in the aggregating layer represented in Fig. 6. In this paper, we call the MLP prediction model which has only one input layer as MLP and the MLP prediction model which is composed of the five sub-MLP models as MLP 2.

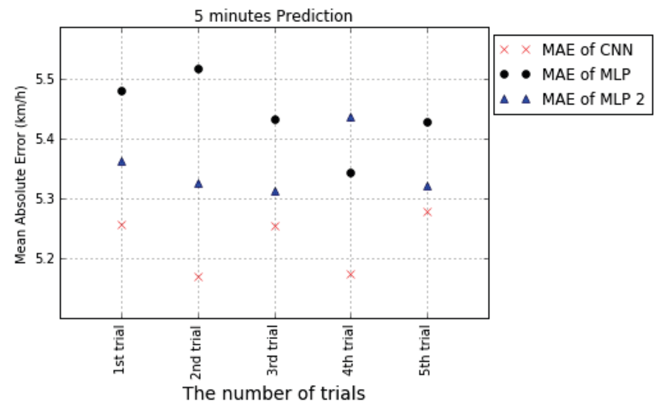
There are several numbers in the corner of boxes representing layers of the two models in Fig. 5 and Fig. 6. These numbers indicate size of nodes in a corresponding layer.

The two MLP models are trained by backpropagation algorithm and ReLU is used as activation function in the two MLP models.

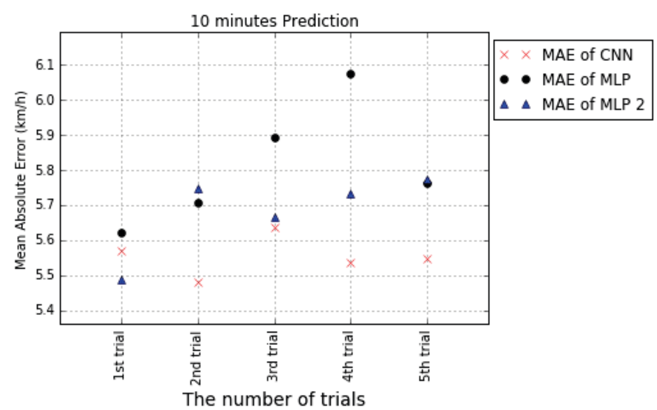
IV. COMPARISON OF MODEL PERFORMACE

To compare performance of the three models, we use Mean Absolute Error (MAE) as evaluation metrics. MAE is derived as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|f(x_i) - y_i\right| \tag{3}$$



(a)



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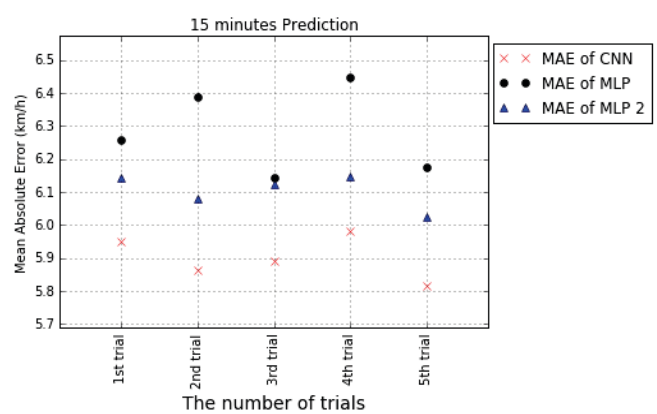

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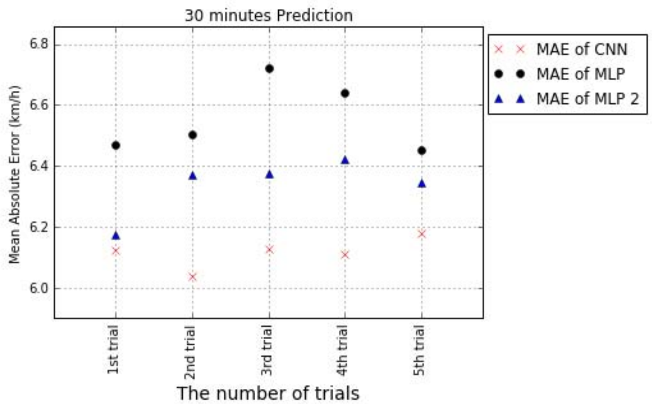

(d)

Figure 7. MAE of the three prediction models under different prediction time intervals

TABLE IV. AVERAGED MAE OF THE THREE MODELS UNDER DIFFERNET PREDICTION INTERVALS

	Prediction Models	Averaged MAE
5 minutes Prediction	CNN	5.23 km/h
	MLP (one input layer)	5.44 km/h
	MLP 2 (Five input layer)	5.35 km/h
10 minutes Prediction	CNN	5.55 km/h
	MLP (one input layer)	5.81 km/h
	MLP 2 (Five input layer)	5.68 km/h
15 minutes Prediction	CNN	5.90 km/h
	MLP (one input layer)	6.28 km/h
	MLP 2 (Five input layer)	6.11 km/h
30 minutes Prediction	CNN	6.12km/h
	MLP (one input layer)	6.56/km/h
	MLP 2 (Five input layer)	6.34km/h

TABLE V. RELATIVE ERROR REDUCTION OF CNN MODEL OVER THE TWO MLP MODELS UNDER DIFFERENT TIME INTERVALS

	RER_{MLP}	$RER_{MLP\text{-}2}$
5 minutes Prediction	3.86 %	2.24 %
10 minutes Prediction	4.48 %	2.29 %
15 minutes Prediction	6.05 %	3.44 %
30 minutes Prediction	6.71 %	3.47 %

where, n denotes size of data used in evaluation, $f(x_i)$ represents a predicted value by the model, and y_i denotes the true traffic speed.

For each model, MAE on the test data is measured 5 times. Fig. 7(a)-(d) shows, MAE of the three prediction models under different time intervals. Fig. 7(a) shows MAE of the three prediction models for 5minutes predictions estimated 5 times. Also, Fig. 7(b), Fig. 7(c), and Fig. 7(d) represent MAE of the three prediction models for 10, 15, and 30 minutes predictions measured 5 times, respectively. And averaged MAE of each model over 5 trials under 4 different prediction time intervals is represented in Table IV. MLP shown in Table IV indicates the MLP prediction model which has only one input layer. MLP 2 shown in Table IV represents the MLP model which is composed of the 5 sub-MLP models.

Comparison result show that CNN-based prediction model outperform the other two MLP models for all prediction time intervals. To evaluate the performance improvement of CNN-based model over the two MLP models, we introduce Relative Error Reduction (RER). There are two types of RER. One is RER_{MLP} which indicates the performance improvement of CNN model over the MLP and the other is $RER_{MLP\text{-}2}$ which indicates the performance improvement of CNN-model over the MLP 2. RER_{MLP} is derived as follows:

$$RER_{MLP} = \frac{MAE_{MLP} - MAE_{CNN}}{MAE_{MLP}} \times 100\,(\%) \tag{4}$$

where, MAE_{MLP} denotes the averaged MAE of MLP and MAE_{CNN} represents the averaged MAE of CNN model. And $RER_{MLP\text{-}2}$ is calculated in similar ways:

$$RER_{MLP-2} = \frac{MAE_{MLP-2} - MAE_{CNN}}{MAE_{MLP-2}} \times 100\,(\%) \tag{5}$$

Where, $MAE_{MLP\text{-}2}$ is the averaged MAE of the MLP 2.

Table V represents RER of CNN model over the two MLP models under different time intervals. RER_{MLP} ranges about 3.9~6.7% for the four prediction time intervals. And $RER_{MLP\text{-}2}$ ranges about 2.2~3.5% for the four prediction time intervals. We can see that the performance of the MLP 2 is higher than the performance of the MLP consistently in the comparison results. The comparison results show that the models composed of multiple sub-models outperform the model without multiple sub-models.

V. CONCLUSION

In this paper, we propose the CNN-based speed prediction model since the CNN-base model has advantages that it can capture local dependencies and is less sensitive to noise in data. And we design the two MLP prediction models for the comparison with CNN-based prediction model. One MLP prediction model has only one input layer which takes temporal data and speed data on the four links all together. The other MLP model, on the other hand, has multiple input layers and consists of the multiple sub-MLP models.

For comparison of the three models' performance, MAE of the three models on the test data is estimated 5 times. The comparison results show that CNN-based model outperforms the other two MLP models for all prediction time internals. Also, it is shown that the models composed of multiple sub-models outperform the model without multiple sub-models.

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