Reliability Engineering and System Safety 217 (2022) 108090

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Evaluation of urban bus service reliability on variable time horizons using a hybrid deep learning method

Tuqiang Zhou [a], Wanting Wu [a], Liqun Peng [a,b], Mingyang Zhang [c,*], Zhixiong Li [d], Yubing Xiong [a], Yuelong Bai [e]

[a] *School of Transportation and Logistics, East China Jiaotong University, Nanchang, China*
[b] *Tsinghua University Suzhou Automotive Research Institute, Suzhou 215134, Jiangsu, China*
[c] *Department of Mechanical Engineering, School of Engineering, Aalto University, Otakaari 4, 02150, Koneteknikka 1, Espoo, Finland*
[d] *Faculty of Mechanical Engineering, Opole University of Technology, Opole 45758, Poland*
[e] *JSTI Nanjing Design Center, Nanjing, China*

A R T I C L E I N F O

Keywords:
Bus service reliability
Time series analysis
Multi-time interval forecasting
Deep learning
VMD-LSTM method

A B S T R A C T

Unreliable transit services can negatively impact transit ridership and discourage passengers from regularly choosing public transport. As the most important content of bus service reliability, accurate bus arrival prediction can improve travel efficiency for enabling a reliable and convenient transportation system. Accordingly, this paper proposes a novel deep learning method, i.e. variational mode decomposition long short-term memory (VMD-LSTM), for bus travel speed prediction in urban traffic networks using a forecast of bus arrival information on variable time horizons. The method uses the temporal and spatial patterns of the average bus speed series. The results show that the VMD-LSTM model outperforms other models on forecasting bus link speed series in future time intervals, whereas the artificial neural network model achieves the worst prediction. In conclusion, the VMD-LSTM method can detect irregular peaks of transit samples from a series of temporal or spatial variations and performs better on major and auxiliary corridors.

1. Introduction

The service reliability of transit systems has significant impacts on providers and users. Unreliable service affects their perception of service quality and transit utility compared to other mode choices[1]. To transit operators, unreliable services will lead to loss of ridership and higher costs to provide additional services to compensate for poor service operations, while to passengers, this situation translates to the perception of service quality and transit utility compared to other mode choices [4]. For buses, an unreliable bus service, characterised by unequal headways or bus bunching for high-frequency services, can lead to longer waiting time and travel time for passengers [15].

In a well-developed transit metropolis, it is necessary to meet the increasing demands of travellers and daily commuters and provide them with reliable bus services to make their travel plans efficient. Therefore, accurate bus arrival prediction has been regarded to improve transit efficiency and competitiveness. Reliable bus arrival prediction within the upcoming short-term/long-term time intervals (i.e., 5 or 10 min) has been a consistent concern for transit agencies to improve the quality of their services. However, a variety of forecasting methods encounter the challenge of uncertain bus speed variations in either a spatial or temporal scale. To improve the reliability of bus arrival prediction on variable time horizons, it is necessary to develop high-precision prediction tools that reflect uncertain bus speed variations.

Although many methods on bus travel time estimation and prediction are similar and overlap with some solutions in the area of probe vehicle data for traffic flow analyses, the bus travel time prediction involves special constraints because transit probes are only collected along the serving route and fixed stop positions [14]. With the increasing numbers of transit vehicles equipped with Global Positioning System devices, a large number of data-based models and theoretical models have been investigated and evaluated; both types of models have achieved modest success rates while having evident limitations [2, 10, 22]. Simple statistical models have been widely applied by transit agencies that either estimate the historical average travel time of traversed buses in the given intervals as the predicted value [17, 19] or only forecast the bus travel time in particular time slots based on the statistics of historical bus travel time information at similar time intervals in the past [6, 16].

* Corresponding author.
E-mail address: mingyang.0.zhang@aalto.fi (M. Zhang).

https://doi.org/10.1016/j.ress.2021.108090
Received 5 May 2021; Received in revised form 14 September 2021; Accepted 17 September 2021
Available online 6 October 2021

The major advantage of these methods is that they are easier to implement than other solutions while being capable of maintaining high computational performance when applied in the real world [21]. However, they follow restrictive assumptions, such that the general traffic conditions between the current and upcoming time intervals are highly similar. This condition rarely occurs in an urban network, where traffic patterns are frequently impacted by external influences, such as unpredictable traffic events or recurrent congestion situations [27].

Another type of data-based bus travel time prediction is explored by inferring the correlations of future bus travel time with current and historical observed data in the space and time domains [28]. In these cases, a large amount of transit automatic vehicle location (AVL) and automatic passenger count data are required to calibrate the coefficients of these models while the knowledge of traffic theory is not needed [24]. Some popular methods for transit travel time prediction under this category are regression methods [18], moving average (MA) methods [31] and Bayesian inference [13]. However, they cannot adapt to real-time variations, and their accuracy heavily relies on the correspondence between observed data and real-time traffic patterns. Moreover, some scholars have applied Kalman filters either as an independent model or in integration with other models for bus arrival time prediction (Achar et al., 2019). Likewise, these models have very limited capabilities in capturing the dynamics of bus travel speeds when the traffic flow is in complex nonlinear situations or the bus dwell time is uncertain.

Furthermore, artificial intelligence (AI) models have been widely used to resolve the high nonlinearities and irregularities of bus samples series in the prediction of bus travel time [20,]. For example, an artificial neural network (ANN) is a distributed processor made up of simple processing units that have a natural propensity for fitting historical bus travel time patterns and using the experimental knowledge for predicting the bus travel time in the next time intervals on the same link [5]. Nevertheless, ANN models have difficulties in generalising predictions due to their overfitting feature; they also depend on researchers' experience to process the training data and determine the structure and parameters of ANN models. Support vector machine (SVM) models are another type of supervised learning that use a hypothetical space of linear functions in a high-dimensional feature space; they are trained with a learning algorithm that can analyse data and recognise patterns in historical data that are used for inferring the tendency of bus travel time series [28, 30]. One of the main challenges of implementing SVM-based models is the high computational requirement for the prediction of large-size datasets. The improvements in computational power, in recent years, has gradually increased the precision of complex AI-based methods for bus arrival prediction [22]. Deep learning is a branch of AI theory that can be applied to exploit the nonlinear dependency in a set of high-dimensional variables; thus, it can be appropriately used to determine the sharp discontinuities of different bus link statuses that arise in complex urban traffic networks [3]. A long short-term memory (LSTM) neural network is a special type of deep learning neural network, which has been proven to be robust for forecasting long-term bus travel time [7, 8, 23, 25].

The performance of these AI-based models has been evaluated and demonstrated to have some advantages over traditional methods [11]. However, these methods also have their shortcomings. For example, ANN and SVM models are sensitive in choosing model structure and parameters, and overfitting is a significant issue. Although the LSTM neural network has a strong ability of learning, generalising and inferring nonlinear time-series data, the real-time implementation of a multi-layer LSTM for predicting the bus arrival information may have high computational requirements that are not always available. To deal with these problems, hybrid time-series analyses and AI models have been recommended to address bus travel time predictions [26]. However, the problem of accurately capturing uncertain bus speed variations under complex traffic conditions persists.

In this study, we propose the variational mode decomposition (VMD)-LSTM model for bus arrival prediction on a concrete transit route with recurrent and non-recurrent traffic conditions. The proposed method is applied to forecast the average bus link speed given a dozen low-frequency bus probes collected from route #707 bus AVL dataset at Wujiang Public Transportation Co., Ltd. (the regional public transport authority in Suzhou, China). The method can provide an accurate bus arrival prediction within different time intervals.

The primary objective of this study is to model the nonlinear patterns of bus travel speed series in recurrent and non-recurrent time intervals. Firstly, a VMD algorithm is applied to extract the regular and irregular patterns of bus travel speed, which can reflect the uncertain conditions produced by random fluctuations in the traffic environment. Then, an LSTM model is combined with the proposed VMD algorithm to forecast beyond a single link and time, i.e. multiple outputs and time steps, with the identified patterns. The proposed VMD-LSTM method can reduce the computational complexity by orders of magnitude as compared to the pure LSTM model while capturing similar bus link travel speed patterns. Therefore, we can identify the following strengths of the proposed solutions in this regard: (1) Conducting real-time bus arrival prediction is more complicated than that of static time-series data because the statistical characteristics of the bus link speed are greatly affected even with a slight change in the traffic flow. Therefore, we apply the VMD autoencoder to capture the intrinsic components and periodic features of the bus speed series. (2) We leverage recent state-of-the-art techniques from time-series analysis and deep learning algorithms and propose a VMD-LSTM model method for predicting the bus arrival time on multiple time horizons ahead, allowing the spatiotemporal transit speed patterns for insight. (3) The overall performance of the LSTM derived models for the bus link speed and travel time prediction is evaluated and compared using different algorithms, i.e. VMD, ensemble empirical mode decomposition (EEMD) and empirical mode decomposition (EMD) as autoencoders, and the results show that VMD is slightly better than the EEMD and EMD algorithms.

The remainder of this paper is arranged as follows: The general method of the proposed VMD-LSTM approach for forecasting the bus arrival time is introduced in Section 2. The detailed modelling process of the VMD-based bus speed pattern analysis and LSTM-based bus travel speed prediction is illustrated in Section 3. The case study performed is discussed in Section 4. Finally, the results and conclusions are presented in Sections 5 and 6, respectively.

2. Framework of VMD-LSTM-based bus arrival prediction

In this section, a time series prediction model, which integrates the LSTM neural network and VMD to decompose the average bus link speed into a series of IMFs as multiple inputs, is explained. The proposed model can forecast the bus travel time in the horizon of multi-time intervals by considering the spatial and temporal variations of collected bus AVL samples. Fig. 1 shows the general framework of the VMD-LSTM based bus arrival prediction, which consists of three steps:

- **Step 1:** The transit AVL data are projected into the network using path inference and a map-matching algorithm [12]. The spatiotemporal bus trajectories in the road network are split into a consecutive time interval and road segment matrix, which is termed as a three-dimensional tensor A_r, in which each axis stands for the road segment, time slot and transit vehicle ID. Each entry in A_r is the average link speed of a bus on a different road segment during a specific time slot. We divide a day into *T* time slots based on a certain interval. Then, we calculate the average bus link travel speed x_(s,t) covering the entire road segment S in each time slot t_i.
- **Step 2:** The VMD algorithm is applied to decompose the time series bus link speed into a set of independent components. Thereafter, the estimated bus link speed series with nonlinear and nonstationary features are decomposed into a finite and small number of IMFs. The differentiated IMF may provide insights for recognising the time series patterns of the bus link travel speed and facilitate the

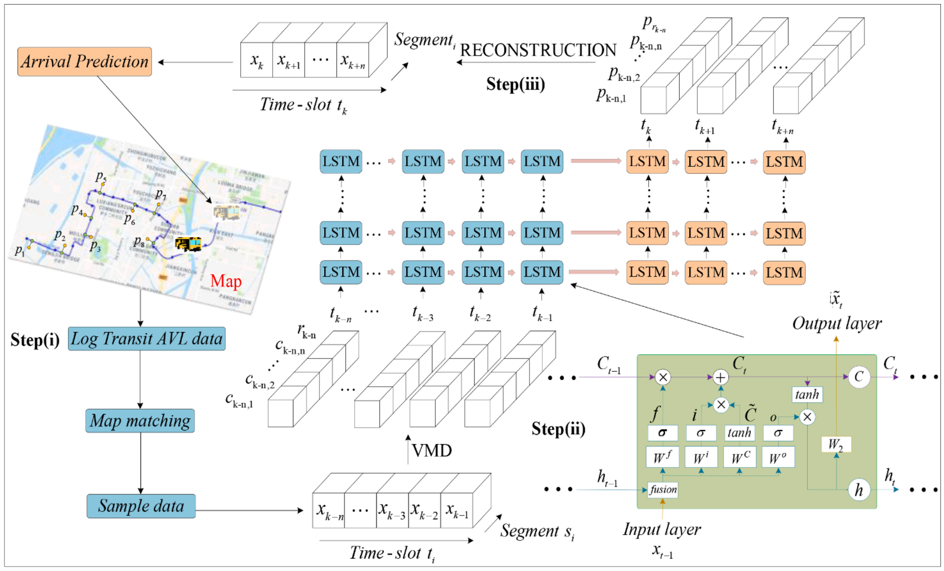


Fig. 1. Framework of the VMD-LSTM for bus arrival prediction.

subsequent bus travel speed forecasting applications. After the IMFs are obtained and each IMF is modelled by the LSTM algorithm, they can be forecasted independently. All the predicted IMFs are aggregated to generate a combined forecasting bus travel speed.

- **Step 3:** The combined procedure is to develop a consensus prediction on immediate historical data. After giving a query path on the scheduled transit route, we update the prediction of its arrival time to the upcoming bus stops at each segment based on the real-time bus locations and subsequent estimated/predicted average link travel speed. More details on the data elements and functionality adopted in this VMD-LSTM layer are given in the following sections.

3. Methodology

3.1. Adaptive bus travel speed series decomposition

The average bus link travel speed series $\{v_{s,t} | s \in N_s,\ t \in N_t\}$ on segment s over the time slot $\{t | t \in \{1,\ 2, \ldots, N_t\}\}$ is regarded as a nonstationary and nonlinear time series. Hence, an ideal prediction to capture the evolution of the bus travel time under complex traffic conditions should consider its variation over time and space. Because the VMD is theoretically capable of processing and extracting the major patterns from nonlinear and non-stationary time series data [9], we use this method to capture the variations of bus speed series over time and space by decomposing raw bus speed samples $v_{s,t}$ into IMF components at different time scales. The IMFs contain typical patterns $l^a_{s,t}$ and, thereby, smoothen the original non-stationary data. The VMD algorithm calculates the IMFs and its centre frequency through the cost function, which is described as follows:

$$min_{\{l^a_{s,t}\},\{w^a_s\}} \left\{ \alpha * \sum_{a=1}^{N_a} \| \vartheta_t \left(l^a_{s,t} * e^{-jw^a_s t} \right) \|_2^2 + \| v_{s,t-} \sum_{a=1}^{N_a} l^a_{s,t}) \|_2^2 \right\} \tag{1}$$

$$v_{s,t} = \sum_{a=1}^{Na} l^a_{s,t} + r_{s,t} \tag{2}$$

This equation can be further extended into a Lagrange formula to transform the constrained variational problem into a non-constrained variational problem.

$$\mathrm{L}\left(\left\{ l^a_{s,t} \right\}, \left\{ w^a_s \right\}, \lambda_{s,t} \right) = \alpha * \sum_{a=1}^{Na} \| \partial_t \left(l^a_{s,t} e^{-jw^a_s t} \right) \|_2^2 + \| v_{s,t} - \sum_{a=1}^{Na} l^a_{s,t} \|_2^2 + \lambda_{s,t} \left(v_{s,t} - \sum_{a=1}^{Na} l^a_{s,t} \right), \tag{3}$$

where $l^a_{s,t}$ is the a^{th} derived component of the original bus link speed series $v_{s,t}$, which is also termed as the IMF; $r_{s,t}$ is a residual variable obtained after N_a-round VMD on $v_{s,t}$; and w^a_s is the corresponding central frequency of each IMF $l^a_{s,t}$. $\lambda_{s,t}$ and α are the penalty factor and quadratic penalty factor, respectively, which ensure the accuracy of the reconstructed $\widehat{v}_{s,t}$ while maintaining the strictness of the constraints. We also define $\widehat{\lambda}_{s,t}$ and $\widehat{v}_{s,w}$ as the Fourier transform of $\lambda_{s,t}$ and $v_{s,t}$, respectively. To solve this variational problem, the algorithm provides the complete

Table 1
Bus travel speed series feature extraction.

Algorithm 1 Bus link speed series feature extraction

Input: Bus link travel speed: $s: \{v_{s,t} | s \in N_s, t \in N_t\}$

Output: IMF set $l_{s,t} = \{l^a_{s,t} | a = 1,2,3,\cdots, N_l\}$

1. Initialise $\{\hat{l}^{a,1}_{s,w}\}$, $\{w^{a,1}_s\}$, $\lambda^l_{s,w}$, $n \leftarrow 0$
2. **For** $a = 1: N_a$ **do**
3. Update $\hat{l}^a_{s,w}$ for all $w \geq 0$:
   $$\hat{l}^{a,n+1}_{s,w} \leftarrow \frac{\hat{v}_{s,w} - \sum_{i=1}^{a} \hat{l}^{i,n+1}_{s,w} - \sum_{i=a+1}^{N_a} \hat{l}^{i,n+1}_{s,w} + \frac{\hat{\lambda}^n_{s,w}}{2}}{1 + 2\alpha(w - w^{a,n}_s)^2}$$
4. Update w^a_s:
   $$w^{a,n+1}_s \leftarrow \frac{\int_0^\infty w |\hat{l}^{a,n+1}_{s,w}|^2 dw}{\int_0^\infty |\hat{l}^{a,n+1}_{s,w}|^2 dw}$$
5. **End for**
6. Dual ascent for all $w \geq 0$:
   $$\hat{\lambda}^{n+1}_{s,w} \leftarrow \hat{\lambda}^n_{s,w} + \tau \left(\hat{v}_{s,w} - \sum_{a=1}^{N_a} \hat{l}^{a,n+1}_{s,w} \right)$$
7. Until convergence:
   $$\sum_{a=1}^{N_a} \left\| \hat{l}^{a,n+1}_{s,w} - \hat{l}^{a,n}_{s,w} \right\|_2^2 / \left\| \hat{l}^{a,n}_{s,w} \right\|_2^2 < \varepsilon$$
8. $l^a_{s,t} = \frac{1}{2\pi} \int_{-\infty}^{+\infty} \hat{l}^a_{s,w} e^{j2\pi wt} dw$
9. Return IMF set $l_{s,t}$

optimisation process in the Fourier domain based on the alternating direction method of multipliers [9], as described in detail in Table 1.

3.2. Transit link travel speed prediction

We collect the average bus speed on link s in previous $\{k\}$ time intervals, which can be described as a vector $v_s = \{v_{s,t+1}, v_{s,t+2}, \cdots, v_{s,t+k}\}$. Then, we apply the VMD method, as illustrated in Section 3.1, to partition the vector v_s into a group of IMFs, which can be indicated as a matrix $x_s = \{x_{s,t+1}, x_{s,t+2}, \cdots, x_{s,t+k}\}$, where $x_{s,t} = \{l^1_{s,t}, l^2_{s,t}, \cdots, l^a_{s,t}, r_{s,t}\}$, t ∈ [1, N_t]. We further apply the LSTM algorithm to predict the vector $\widetilde{x}_{s,t+k+1} = \{\widetilde{l}^1_{s,t+k+1}, \widetilde{l}^2_{s,t+k+1}, \cdots, \widetilde{l}^a_{s,t+k+1}, \widetilde{r}_{s,t+k+1}\}$, as shown in Table 2. The main model formulas in this regard are as follows.

$$f_{s,t} = \sigma\left(w^f_1 \cdot l_{s,\{k\}} + w^f_h \cdot \widetilde{l}^i_{s,t+k} + b_f\right) \tag{4}$$

$$i_{s,t} = \sigma\left(w^i_1 \cdot l_{s,\{k\}} + w^i_h \cdot \widetilde{l}^i_{s,t+k} + b_i\right) \tag{5}$$

$$C_{s,t} = \tanh\left(W^C_1 \cdot l_{s,\{k\}} + W^C_h \cdot \widetilde{l}^i_{s,t+k} + b_C\right) \tag{6}$$

$$C_{s,t} = i_{s,t} \cdot \widetilde{C}_{s,t} + f_{s,t} \cdot C_{s,t-1} \tag{7}$$

$$O_{s,t} = \sigma\left(W^0_1 \cdot l_{s,p\{k\}} + W^o_h \cdot \widetilde{l}^i_{s,t+k} + b_o\right) \tag{8}$$

$$\widetilde{l}^i_{s,t+k+1} = o_{s,t} * \tanh\left(C_{s,t}\right) \tag{9}$$

Here, the vector $l_{s,\{k\}} = \{l^i_{s,t+1}, l^i_{s,t+2}, \cdots, l^i_{s,t+k}\}$ represents the i^{th} IMF of the bus travel speed pattern on link s in the previous $\{k\}$ time interval, and $\widetilde{l}^i_{s,t+k}$ represents the predicted i^{th} IMF from the previous k time slot. The core idea of using LSTM to forecast the bus link speed information is mainly based on the special gate structure of this model, which is capable of optionally selecting correlated historical patterns in previous time-series data through the cell state and passing them to next inferring procedures. $i_{s,t}$ is the value for which we may update the cell state in this prediction, and $f_{s,t}$ is the value determining whether the previous cell state $C_{s,t-1}$ in time interval $t-1$ can be passed in the next prediction. $\widetilde{C}_{s,t}$ is the new state in the current prediction, which could be added to the cell state $C_{s,t}$. The output is $\widetilde{l}^i_{s,t+k+1}$, which should be denormalised to reflect the predicted i^{th} IMF of the bus travel speed on the link s in the next $k+1$ time interval. Then, we reconstruct $\widetilde{l}^i_{s,t+k+1}$ and $\widetilde{r}_{s,t+k+1}$ and predict the average bus link travel speed $\widetilde{v}_{s,t+k+1}$ in the next time slot, as shown in Eq. (10).

Table 2
Bus travel speed prediction.

Algorithm 2 Bus link travel speed prediction

Input: Bus link speed sample dataset $\mathrm{v} = \{v_{s,t}\}_{t=1}^{TL}$

LSTM model training setting:
Max_epoch = 500,
Hidden layer = 1,
Hidden layer neurons = 64,
Batch size = 20,
Learning rate η = 0.01,
Error threshold ε = 0.001,

Output: Predicted bus link speed $\tilde{v}_{s,t+k+1}$

1. Initialisation: Initialise Θ randomly
2. Input bus speed samples v_s
3. Partition v_s into IMFs x_s
4. Estimate the LSTM model input $l_{s,\{k\}}$
5. **While** *epoch* < max *epoch* **do**
6. **For** $i = 1{:}1{:}|x_{s,t}|$
   $f_{s,t} = \sigma(W^f_1 \cdot l_{s,\{k\}} + W^f_h \cdot \tilde{l}^i_{s,t+k} + b_f)$
   $i_{s,t} = \sigma(W^i_1 \cdot l_{s,\{k\}} + W^i_h \cdot \tilde{l}^i_{s,t+k} + b_i)$
   $\tilde{C}_{s,t} = tanh(W^C_1 \cdot l_{s,\{k\}} + W^C_h \cdot \tilde{l}^i_{s,t+k} + b_c)$
   $C_{s,t} = i_{s,t} \cdot \tilde{C}_{s,t} + f_{s,t} \cdot C_{s,t-1}$
   $O_{s,t} = \sigma(W^o_1 \cdot l_{s,\{k\}} + W^o_h \cdot \tilde{l}^i_{s,t+k} + b_o)$
7. **End for**
8. $\tilde{v}_{s,t+k+1} = \sum_{a=1}^{|\tilde{x}_{s,t+1}|-1} \tilde{l}^a_{s,t+k+1} + \tilde{r}_{s,t+k+1}$
9. $L^{epoch+1} = L(v_{train\_output}, \tilde{v}_{train\_output})$
10. **If** $|L^{epoch} - L^{epoch+1}| < \varepsilon$ **then**
11. Output Θ
12. Break
13. **End if**
14. **End While**

$$\widetilde{v}_{s,t+k+1} = \sum_{a=1}^{\left|\widetilde{x}_{s,t+1}\right|-1} \widetilde{l}^{a}_{s,t+k+1} + \widetilde{r}_{s,t+k+1} \tag{10}$$

The w_1^f, w_1^i, w_1^o and w_1^c are the coefficients of $l_{s,\{k\}}$; w_h^f, w_h^i, w_h^o and w_h^c are the coefficients of $\widetilde{l}^{i}_{s,t+k}$; and b_f, b_i, b_o and b_c are offsets. All these parameters can be trained in a supervised manner to achieve a good prediction performance based on our sample dataset $v = \{v_{s,t}\}_{t=1}^{TL}$, which has been separated to the model training dataset $v_{train} = \{v_{s,t}\}_{t=1}^{TL_1}$ and test dataset $v_{test} = \{v_{s,t}\}_{t=TL_1+1}^{TL}$, in which TL is the total number of samples. We conduct the bus link travel speed prediction on different time intervals (i.e. 5 and 10 min) by setting k groups of the original sample data as one training sample $v_{train\_input} = \{v_{s,t}, v_{s,t+1}, \cdots, v_{s,t+k-1}\}_{t=1}^{TL_1/k}$ and $v_{test\_output} = \{v_{s,t+k}\}_{t=1}^{TL_1/K}$. The model parameters will be optimised at max_epoch times until the mean square error of $\widetilde{v}_{train\_output}$ and v_{train_output} achieve the minimum value, as shown below:

$$\Theta = \mathrm{argminL}\left(v_{train\_output}, \widetilde{v}_{train\_output}\right) \tag{11}$$

$$\mathrm{L}\left(v_{train\_output}, \widetilde{v}_{train\_output}\right) = \sqrt{\frac{\sum_{t=k}^{TL_1}\left(v_{s,t+k+1} - \widetilde{v}_{s,t+k+1}\right)}{2(TL_1/k)}} \tag{12}$$

3.3. Transit arrival time prediction

In this section, the real-time transit link travel speed and bus positions are collected. Then, we predict the transit arrival time at downstream stops in different time horizons, i.e. 5, 10 and 15 min. As shown in Fig. 2, we use the historical bus link travel speed series $v_s = \{v_{s,1}, v_{s,2}, \cdots, v_{s,k}\}$ to predict the bus travel time $\widetilde{v}_{s_i,k+m}$ on each downstream link s_i in the next time interval based on our proposed VMD-LSTM method. After combining the distance on the route between the real-time bus position and upcoming bus stops, the bus arrival time at the referring locations can be calculated.

The method for calculating the predicted bus arrival time can be found in Algorithm 3 (Table 3). We firstly detect the real-time bus location p on the link s_p, bus stop location z and predicted bus spatio-temporal link speed $v_{s,t}$, $s \in [1, N_s]$, $t \in [1, k]$. Thus, the segments n_z between the current bus position and an upcoming bus stop can be determined. Then, we further predict the bus link travel speed $\widetilde{v}_{s,k+m}$ that the bus will traverse through the link s within the time interval m. Consequently, the bus arrival time T_z will be calculated as follows:

Table 3
Transit arrival time prediction.

Algorithm 3 Transit arrival time prediction

Input: Real-time location p, timestamp T_p,
Bus stop location z
Bus link travel time $\tilde{v}_{s,k+m}$
Link distance information D_s

Output: Bus arrival time T_z

1. Determine the segments n_z between p and z
2. **If** $n_z = 0$
3. Estimate the distance $D_{p,z}$
4. Forecast the bus arrival time as: $T_p + \frac{D_{p,z}}{\tilde{v}_{s_p,m}}$
5. **Else if** $n_z \geq 1$
6. Estimate the distance D_{p,s_p} and $D_{s_p+n_z,z}$
7. Forecast the bus arrival time as: $T_p + \frac{D_{p,s_p}}{\tilde{v}_{s_p,m}} + \sum_{s=s_p+1}^{s_p+n_z-1}\frac{D_s}{\tilde{v}_{s,m}} + \frac{D_{s_p+n_z,z}}{\tilde{v}_{s_p+n_z,m}}$
8. **End if**

$$T_Z = \begin{cases} T_P + \dfrac{D_{P,Z}}{\widetilde{v}_{s_p,m}}, n_z = 0 \\ T_P + \dfrac{D_{P,S_P}}{\widetilde{V}_{S_P,m}} + \displaystyle\sum_{s=s_p+1}^{s_p+n_z-1} \dfrac{D_S}{\widetilde{v}_{s,m}} + \dfrac{D_{S_P+n_z,z}}{\widetilde{v}_{s_p+n_z,m}}, n_z \geq 1 \end{cases}, \tag{13}$$

where T_p is the collected real-time bus time stamp, $D_{p,z}$ is the distance between the current bus position and upcoming bus stop if both are on the same link, D_{p,s_p} is the distance of the bus location to the end of its current link, $D_{s_p+n_z,z}$ is the distance of the target bus stop position z to the start point of the link and D_s is the distance of link s.

3.4. Benchmarks and parameter setting

The proposed method is empirically evaluated by monitoring data deployed in production by the public transport authority and compared to existing ANN models and LSTM-derived models with different autoencoders, i.e. EEMD and EMD, which decompose the time-series samples to obtain certain and uncertain characteristics from either

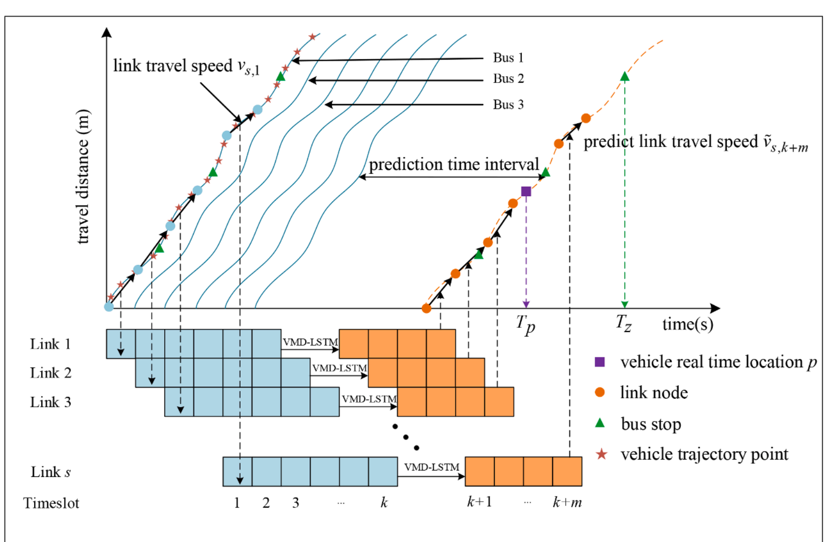


Fig. 2. Time–space diagram of the bus arrival time prediction.

temporal or spatial variations. The procedures of the EEMD-LSTM and EMD-LSTM models are similar to the proposed VMD-LSTM model in the time-series data analysis. Nevertheless, the application of EMD and EEMD as autoencoders helps to decompose and extract typical patterns from bus link speed series, whereas the pure LSTM model for bus link speed prediction without applying any autoencoder processes the raw sample series.

The performance of the VMD-LSTM method for the transit link speed and bus arrival forecasting on different time horizons is evaluated and compared against benchmark methods, i.e. EEMD-LSTM model, EMD-LSTM model, pure LSTM model and ANN model. All models are trained using the same dataset as the VMD-LSTM model and implemented with similar LSTM architecture as the predictor. The measurements for monitoring the ground truth of the bus operation status on individual links are collected and processed at 5, 10 and 15 min intervals using non-publicly accessible endpoints at the transport authority. The experiments are performed under the optimal model parameter set. In this study, we configure the ANN model as a single hidden layer neural network, and the number of the hidden layers is set in accordance with the number of the LSTM-derived models.

The number of neurons in the ANN model and LSTM-derived model is set at 100. The LSTM models are trained using an Adam optimizer with a learning rate of 0.001, a batch size of 20 and an epoch of 200. The input features are defined as four sequential bus speed series on the same link from previous time intervals, and each time interval is set to be 5 min long. Based on this, we predict the upcoming bus link speed on horizons of 5, 10 and 15 min.

4. Experiments

4.1. Experimental data

In this section, the bus route information and real-time bus AVL data are collected to evaluate the model performance. The research study is focused on the #707 bus route at Suzhou, China, as shown in Fig. 3. We also attempt to apply the proposed and benchmark methods on the same condition in urban and non-urban areas and assess their performance where the transit speed pattern is inconsistent due to the variable traffic flow. The total length of this bus route, starting from Tongli station and terminating to Lize Road station, is 17.74 km traversing through 34 bus stops in urban and suburban areas. amongst them, there are 16 road links from Yunliqiao West to the terminal station, i.e. Lize Road station, with 12 signal intersections. The total length of this partial route is 6.60 km, and the average distance between any internal consecutive bus stops is 0.41 km. The transit systems are likely to suffer delays in these segments because the traffic flow becomes high in daily peak hours. The rest of the 17-road links, from the Tongli departure station to Yunliqiao West, have a total length of 11.14 km, and the average distance between two successive bus stops is 0.66 km. There are few bus delays in most cases on these route links.

In this work, we collect 387 bus trajectories on the designed route; each bus trajectory involves almost 300 to 400 raw transit AVL data, including bus ID, timestamp, vehicle location (longitude and latitude) and real-time velocity. All the information is transmitted back to the transit operation monitoring system over the General Packet Radio Service communication. As suggested by Baek and Sohn [3], inferring traffic conditions from positioning data requires five steps, i.e. map matching, path identification, probe filtering, travel time allocation and travel time aggregation. A practical method to estimate the transit link travel speed using raw bus AVL data sources is applied to reproduce bus link speed samples, as shown in Table 4, which include vehicle ID (BUS_ID), link node (F_NODE and T_NODE) and length (LINK_LENG), and the timestamps of vehicles entering and exiting the link. Then, we calculate the bus travel time and average travel speed on the link. F_NODE and T_NODE are the origin and destination of the bus route, respectively. The details of the transit sample processing will not be explained in this work.

To investigate the prediction effort of the models on specific time intervals or segments that buses operate with irregular speed, our analysis focuses on the time slots when the transit speed is largely affected by the surrounding environment, i.e. traffic congestion in the morning and afternoon peaks, or unanticipated events.

4.2. Evaluation and validation

The proposed method is empirically evaluated by monitoring data deployed in the production by the public transport authority and compared with the traditional LSTM model, linear regression and SVM, which consider either the temporal or spatial variation. Furthermore, we define two indexes, i.e. mean absolute error (MAE) and root mean squared error (RMSE), to evaluate the accuracy of bus travel speed prediction and bus arrival time prediction. The MAE value can be applied to represent the absolute deviation between the predicted results and ground truth, whereas the RMSE can be used to examine the extent of prediction deviation given the reference speed and bus arrival time information, as shown below.

$$\mathrm{MAE} = \frac{1}{N}\sum_{k=1}^{N}\left|v_{prediction} - v_{observation}\right| \tag{14}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{k=1}^{N}\left(v_{prediction} - v_{observation}\right)^2}{N}} \tag{15}$$

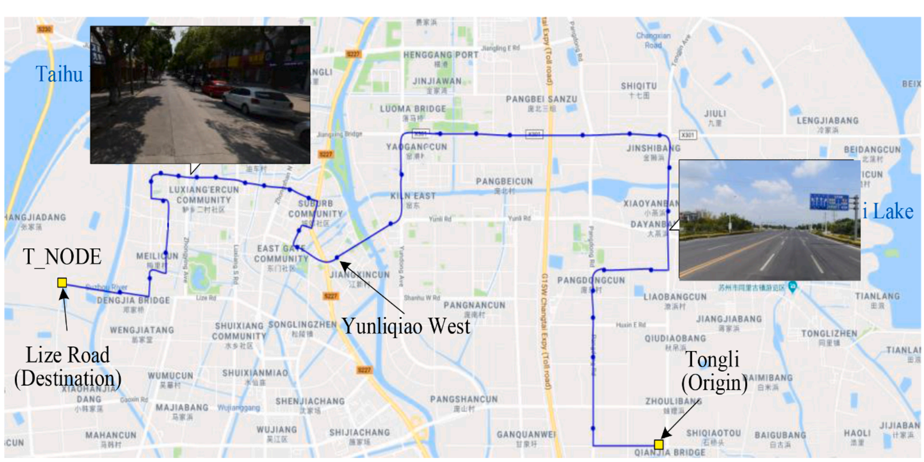


Fig. 3. Experiment on the transit route of bus #707.

Table 4
Bus link travel speed samples.

BUS_ID	LINK_TRAVEL_INFORMATION F_NODE	FNODE_TIME	T_NODE	TNODE_TIME	LINK_LENG (km)	T_SPEED (m/s)
3365	Tongli	1,495,756,290	Wujiang Hospital	1,495,756,390	1.12	11.2
3367	Wujiang Hospital	1,495,757,113	Pangdong Road	1,495,757,178	0.78	12.0
…						
3259	Yunliqiao East	1,495,753,458	Yunliqiao West	1,495,753,571	0.87	7.6
…						
3289	Suzhou River Road East	1,495,771,501	Lize Road	1,495,771,560	0.77	12.8

$$R^2 = 1 - \frac{\sum_{k=1}^{N}\left(v_{prediction} - v_{observation}\right)^2}{\sum_{k=1}^{N}\left(v_{prediction} - \overline{v}_{observation}\right)^2} \tag{16}$$

Here, N is the number of predicted/observed samples, $v_{prediction}$ is the predicted bus link speed based on our evaluation models and $v_{observation}$ is the average value of the bus link speed $\overline{v}_{observation}$ collected from the transit authority database. The formula R^2 represents the good fitting effect of the applied model when it approaches 1 faster than other models.

5. Results and discussion

This paper proposes a predictive analytics method that brings together knowledge from deep learning for the evaluation of urban bus service reliability on variable time horizons. The results and findings from the case study are concluded, together with discussions.

5.1. Model performance analysis

As described in Section 3.1, we collect the average bus speed on the link in previous time intervals, which can be described as a vector. Then, we apply the VMD method to partition the vector into a group of IMFs. We further apply the LSTM algorithm to predict the vector, namely bus link speed. We compare the overall performance of the bus link speed and travel time prediction based on the models mentioned above, as shown in Table 5. The results show that the VMD-LSTM model generally outperforms other models on the forecasting bus link speed series in future time intervals, whereas the ANN model achieves the worst prediction effort, especially on long-term time horizons, i.e. 15 min. This result is most likely attributed to the LSTM derived models that are more adaptive to the dynamic features of the transit operation status under the impact of the external traffic environment than the ANN model. Although the difference between the VMD-LSTM model and baseline models for short-term prediction seems to be nonsignificant, the evaluation indexes, i.e. MAE, RMSE and R^2, are estimated on the whole spatial and temporal spaces, where most of the transit operations are consistent and smooth, averaging their errors.

In this section, we inspect a bus link speed matrix of predictions at $t + 10$ min on a random weekday as an example (plotted in Fig. 4), which obtains a detailed view of how the proposed and baseline models perform at the micro level, i.e. in each time interval and link, respectively. As shown in Fig. 4, the average bus link speed is delayed and fluctuates frequently during peak hours, i.e. 7:00–9:00 AM and 4:30–7:00 PM, than in normal hours; this condition leads the ANN model to overpredict or underpredict the bus link speed series in peak time intervals. The ANN model increases its MAE by 12.68% and RMSE by 27.47% as compared to the LSTM model in the 10 min horizon prediction. These differences were further widened when the prediction was implemented on a 15 min horizon. There is also heavy traffic congestion during afternoon hours, in which the ANN model cannot accurately predict the bus link speed. Meanwhile, the pure LSTM and LSTM-derived models became much closer to the ground truth during the peak hours. The general prediction performance of the EEMD-LSTM model is slightly better than that of the VMD-LSTM model in the morning peak hours, whereas the opposite occurs in the afternoon peak hours. However, both models can predict irregular bus speed patterns in the congested traffic flow and adjust to it to some extent. In addition, in this prediction, the VMD-LSTM model reduces on average the MAE by 44.02% and RMSE by 49.07% compared to the EMD-LSTM model and MAE by 34.19% and RMSE by 32.39% compared to the pure LSTM model. The performances of the LSTM-derived models and ANN model are slightly different in regular time slots, in which most bus link speed series are consistent and smooth. Nevertheless, the VMD-LSTM model still predicts the best, which indicates that the autoencoded LSTM models are highly effective for analysing bus sample series when the traffic patterns dynamically deviate in particular time intervals, i.e. when the urban network is under pressure.

Furthermore, we investigated the performance of the bus travel time prediction on two typical segments in a regular single weekday based on the analysis of bus link speed series, as shown in Fig. 5. The prediction in Fig. 5(a) is implemented on route segment #31, which is a 550-m-long link with a one-way lane, where traffic congestions frequently occur in morning and afternoon peak hours. The evaluation results show that the VMD-LSTM, EEMD-LSTM and EMD-LSTM models increase their prediction performance over the pure LSTM and ANN models when the traffic is under pressure. The VMD-LSTM model reduces MAE by 5.18%, 8.98% and 54.02% compared to the EEMD-LSTM, EMD-LSTM and pure LSTM models, respectively, in this prediction. In daily peak hours, although the LSTM-derived models and ANN model undergo a significant decrease in travel time prediction of up to 15 s, the VMD-LSTM model degrades its average performance to a lesser extent as compared to other baseline approaches.

The prediction in Fig. 5(b) is conducted on route segment #7, which is a 770-m-long link with three well-conditioned segments with a designed average speed of 60 km/h and isolation zone between vehicle and non-vehicle participants. The average bus travel time is less impacted, and the transit vehicle delay is mitigated on this link.

Table 5
Bus link speed prediction of the proposed and baseline models.

Model	$t + 5$ min MAE	RMSE	R^2	$t + 10$ min MAE	RMSE	R^2	$t + 15$ min MAE	RMSE	R^2
VMD-LSTM	0.156	0.190	0.952	0.281	0.382	0.927	0.449	0.593	0.814
EEMD-LSTM	0.141	0.205	0.934	0.285	0.409	0.916	0.463	0.568	0.810
EMD-LSTM	0.299	0.412	0.906	0.502	0.750	0.804	0.678	0.744	0.693
Pure LSTM	0.286	0.470	0.851	0.427	0.565	0.695	0.632	0.847	0.602
ANN	0.408	0.569	0.827	0.489	0.779	0.596	0.787	0.853	0.588

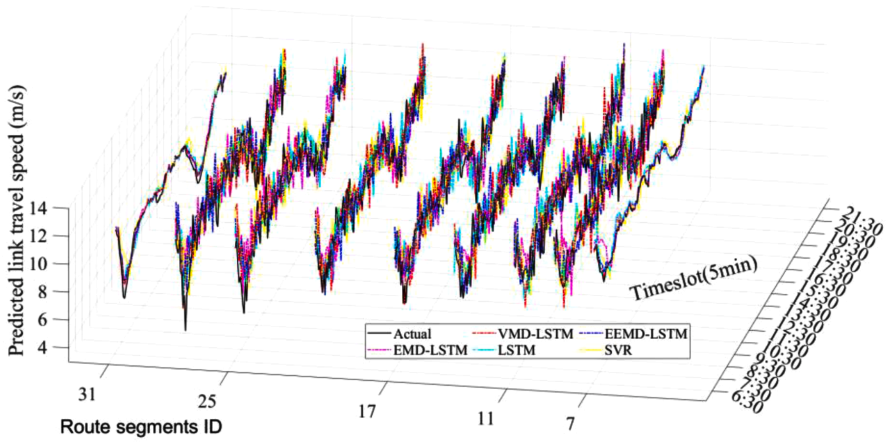
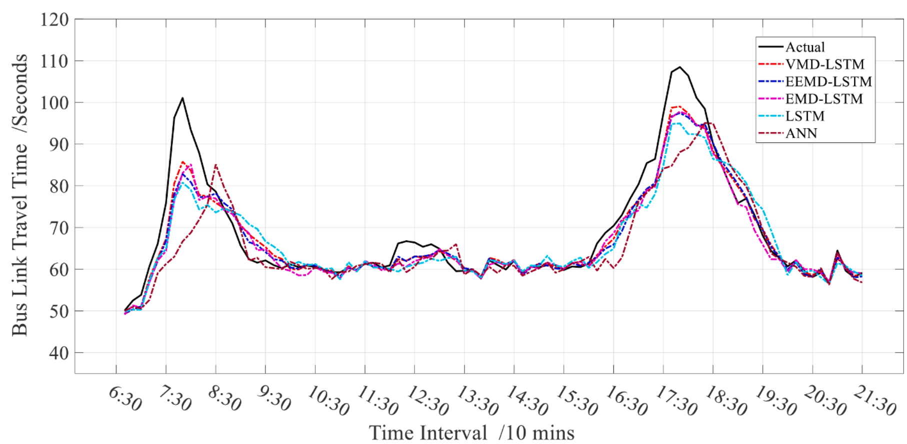
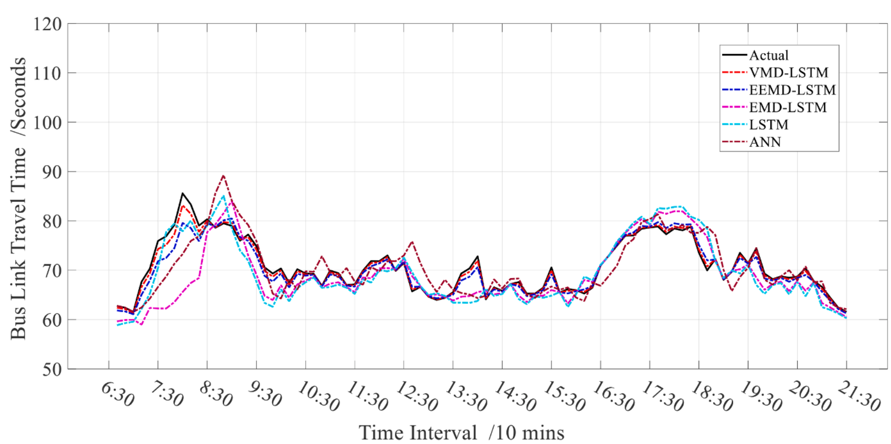


Fig. 4. Bus link travel speed prediction for 10 min intervals.



(a) Predicted bus link travel time on segment #31



(b) Predicted bus link travel time on segment #7

Fig. 5. Predicted transit link travel time over a single day (in the test dataset).

Similarly, the peak hour evaluation shows a good prediction performance of the VMD-LSTM model, which reduces a lesser error gap than the other baseline models. These results demonstrate that the autoencoded LSTM models can improve the bus travel speed and travel time prediction and make them more accurate than the pure LSTM models when the bus has very irregular speed. Moreover, the VMD (as the autoencoder) shows slightly better results than the EEMD and EMD algorithms. However, the LSTM-derived models and pure LSTM models significantly increase the MAE and RMSE of prediction results on the time horizons over 15 min.

5.2. *Performance evaluation of the VMD-LSTM deep learning method*

The predicted bus link speed series and real-time bus positions can be obtained and applied to forecast the bus arrival time at downstream stops on different time horizons. As shown in Fig. 2, we use the historical bus link travel speed series to predict the bus travel time on each downstream link in the next time interval based on our proposed VMD-LSTM method. After combining the distance on the route between real-time bus position and upcoming bus stops, the bus arrival time to the referring locations can be calculated. In this study, the bus arrival predictions are limited to daytime, between 06:30 and 21:30, and they are accumulated downstream on a journey level to simulate the use for real-time bus arrival/departure time prediction. Fig. 6 shows the overall performance of the proposed model and other models. For the input features, we choose the interval length according to the bus arrival time in the upcoming 5, 10 and 15 min. Furthermore, the LSTM-derived models are evaluated by setting the number of hidden layers to 50, 100 and 200, whereas the ANN is a single hidden layer neural network, and the number of its neurons in the hidden layer is set correspondingly when compared with the LSTM models. All models are trained using an Adam optimiser with a learning rate of 0.001, a batch size of 20 and an epoch of 200. When the number of hidden layers in the LSTM-derived model is set to 100, they achieve the best prediction performance on the bus arrival prediction in different time steps. As shown in Fig. 6, when the bus arrival time is within 5 min, the VMD-LSTM model shows slightly fewer prediction errors compared to other LSTM derived models. Moreover, it reduces the MAE by 18.36%, 30.2% and 30.54% compared to the EEMD-LSTM, EMD-LSTM and pure LSTM models, respectively, and 38.21% concerning the ANN model when the upcoming bus arrival time is within 10 min. The overall performance of these applied models has an evident increase in prediction error when the bus arrival is within 15 min. However, the bus dwelling time at bus stops is not estimated and considered in this study, which may cause prediction deviation along with the accumulation of the bus travel time to the downstream stops.

Finally, we compare the computational complexity of training the LSTM-derived models and ANN model [32]. The ANN model can be calculated within 5 min for the full transit dataset on 33 links within 4 weeks. The training of the pure LSTM and LSTM-derived models can be achieved for the same dataset in over 10 min on a commercial laptop (Intel(R) Core (TM) i5–6200 U CPU, 4 GB RAM). Essentially, the autoencoder algorithms in the input features have little influence on the computational performance, but the prediction results can be significantly improved by introducing the autoencoders. Furthermore, although the simple historical average models are still popular in the industrial systems due to their computational efficiency, the more complex models are scalable, and their improved accuracy is desirable despite being more computationally expensive.

Overall, the model performance analysis and performance evaluation indicate that the proposed method based on the deep learning method has potential applications in the evaluation of urban bus service reliability on variable time horizons, which have significant impacts on providers and users.

6. Conclusions

In this study, we evaluate an integrated LSTM deep learning method for transit arrival prediction and its performance on this application by applying different algorithms as autoencoders. Particularly, the VMD is employed to decompose the raw bus link speed series into several sublayers, and the LSTM network is adopted as the predictor of each sublayer. The proposed method can reduce computational complexity by orders of magnitude as compared to the pure LSTM model while capturing similar bus link travel speed patterns. To validate the forecasting capacity of the proposed hybrid VMD-LSTM model, four other forecasting models are implemented on the bus travel speed time series. The models consist of the EEMD-LSTM, EMD-LSTM, pure LSTM and ANN models.

Firstly, we conclude that the VMD-LSTM model may provide satisfactory bus speed forecasting results in the involved bus link speed time series. Secondly, the combination of time features and autoencoder algorithms, i.e. VMD, EEMD and EMD, improve the sensitivity of the LSTM neural network to time because the modal decomposition method can separate multiple time-series features from the raw operating bus link speed data. Thus, the LSTM model can fully perceive the potential timely change of the bus link speed in the next time interval, which improves the prediction accuracy of the bus arrival time. Thirdly, the VMD method outperforms other popular autoencoder methods and promotes the bus speed forecasting accuracy and stability of the LSTM network even more significantly during the peak hours, where the urban bus transport network is under stress. Lastly, amongst all the models, the VMD-LSTM model has the best performance for short-term and long-term predictions.

Owing to data limitations, only one bus line in Suzhou is selected as a case study, and the applicability and effectiveness of the model should be further tested in more complex traffic conditions. Meanwhile, the benchmark methods are restricted to few traditional neural network structures, and more diversified options are needed. Despite the limitations, the proposed VMD-LSTM model has provided a novel process for bus arrival prediction.

Although the VMD-LSTM model is more computationally expensive than simple historical average models, given the state of modern computational hardware, it is indeed possible to apply it to an urban bus network for independent routes. Even with commodity hardware, we can retrain the route used in this experiment in less than 20 min and easily retrain the model daily. Given the results of our proposed model, we are currently pursuing the deployment of the model in field applications in collaboration with the transit authority in Suzhou.

For future work, we plan to investigate the deepening of the VMD-LSTM model to incorporate travel speed and travel time applications in more complex traffic situations to improve its prediction

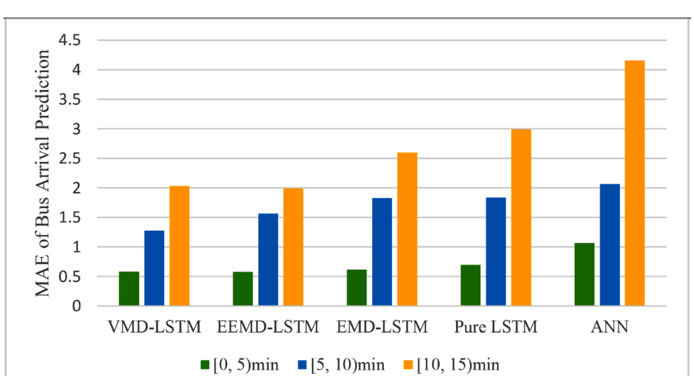


Fig. 6. Bus arrival time prediction of the proposed and baseline models.

performance. In addition, we are currently keeping in touch with traffic control departments in different cities (e.g. Nanchang and Wuhan) so that more experiments can be performed soon. In conclusion, this study can help build a more stable and reliable real-time information transportation system, which is one of the key elements for realising Mobility as a Service.

CRediT authorship contribution statement

Tuqiang Zhou: Visualization, Investigation, Writing – original draft, Data curation, Methodology, Writing – review & editing, Funding acquisition, Project administration. **Wanting Wu:** Methodology, Writing – review & editing. **Liqun Peng:** Validation, Writing – review & editing. **Mingyang Zhang:** Conceptualization, Writing – original draft, Methodology, Writing – review & editing. **Zhixiong Li:** Conceptualization, Writing – original draft, Writing – review & editing. **Yubing Xiong:** Supervision. **Yuelong Bai:** Writing – review & editing, Data curation.

Declaration of Competing Interest

All authors declare that they have no actual or potential competing financial interests or personal relationships.

Acknowledgments

This research is jointly supported by National Nature Science Foundation of China (Grant No. 52062015 and 51708218) and Jiangxi Provincial Major Science and Technology Project-5G Research Project (Grant No. 20193ABC03A005), and Narodowego Centrum Nauki, Poland (No. 2020/37/K/ST8/02748).

Appendix A. Data availability and open source code implementation

- The complete analysis performed and the creation of figures in the paper can be reproduced by running the function *test.m*: https://github.com/zhangmingyangliu/A-VMD-LSTM-Deep-Learning-Framework-for-Bus-Arrival-Prediction-on-Variable-Time-Horizons.V1.git.
- This repository contains also all datasets preprocessed and structured as they were used: https://github.com/zhangmingyangliu/A-VMD-LSTM-Deep-Learning-Framework-for-Bus-Arrival-Prediction-on-Variable-Time-Horizons.V1/blob/main/code.

Appendix B. Abbreviations and variables

Abbreviation

Abbreviation	Description	Abbreviation	Description
VMD	Variational Mode Decomposition	ANN	Artificial Neural Network
LSTM	Long Short-Term Memory	SVM	Support Vector Machine
IMF	Intrinsic Mode Function	EEMD	Ensemble Empirical Mode Decomposition
AVL	Automatic Vehicle Location	EMD	Empirical Mode Decomposition
GPS	Global Position System	ADMM	Alternate Direction Method of Multipliers
APC	Automatic Passengers Count	GPRS	General Packet Radio Service
MA	Moving Average	MAE	Mean Absolute Error
KF	Kalman Filters	RMSE	Root Mean Squared Error
AI	Artificial Intelligence	ANN	Artificial Neural Network
EMD	Empirical Mode Decomposition	SVM	Support Vector Machine
ADMM	Alternate Direction Method of Multipliers	EEMD	Ensemble Empirical Mode Decomposition

Glossary of variables

Variables	Defintions	Variables	Defintions
x_(s,t)	Average bus link travel speed	w_s^a	Corresponding central frequency of each IMF $l_{s,t}^a$
S	Road segment	$\lambda_{s,t}$	Penalty factor
t_i	Time slot	α	Quadratic penalty factor
$v_{s,t}$	Raw bus speed samples	$\widehat{\lambda}_{s,t}$	Fourier transform of $\lambda_{s,t}$
$l_{s,t}^a$	The a^{th} derived component of original bus link speed series $v_{s,t}$	$\widehat{v}_{s,w}$	Fourier transform of $v_{s,t}$
$r_{s,t}$	Residual variable	$\{k\}$	Time interval
v_{test}	Testing dataset	$l_{s,\{k\}}$	The i^{th} imf of bus travel speed pattern on link s in the previous $\{k\}$ time interval
$\widetilde{C}_{s,t}$	New state in current prediction	$\widetilde{l}_{s,t+k}^{i}$	The predicted i^{th} imf passed from previous k time slot
$\widetilde{l}_{s,t+k+1}^{i}$	Predicted i^{th} imf of bus travel speed on the link s in next $k+1$ time interval	$C_{s,t-1}$	Cell state
w_1^f, w_1^i, w_1^o, w_1^c	Coefficients of $l_{s,\{k\}}$	$i_{s,t}$	Cell state update value
w_h^f, w_h^i, w_h^o, w_h^c	Coefficients of $\widetilde{l}_{s,t+k}^{i}$	$f_{s,t}$	Determining value
b_f, b_i, b_o, b_c	Offsets	T_p	Collected real-time bus time stamp
TL	Total number of samples	$D_{p,z}$	Distance between current bus position and upcoming bus stop
v	Sample dataset	D_{p,s_p}	Distance of bus location to end of its current link
v_{train}	Training dataset	$D_{s_p+n_z,z}$	Distance of target bus stop position z to the start point of the link
s_i	Downstream link	D_s	Distance of link s
p	Real time bus location on the link s_p	N	Number of predicted or observed samples
z	Bus stop location	$v_{prediction}$	Predicted bus link speed
T_z	Bus arrival time	$v_{observation}$	Average value of bus link speed $\overline{v}_{observation}$ collected from the transit authority database

References

[1] Achar A, Bharathi D, Kumar BA, Vanajakshi L. Bus arrival time prediction: a spatial kalman filter approach. IEEE Trans Intell Transp Syst 2020;21(3):1298–307.
[2] Atlinkaya M, Zontul M. Urban bus arrival time prediction: a review of computational models. Int J Recent Technol Eng 2013;2(04):164–9.
[3] Baek J, Sohn K. Deep-learning architectures to forecast bus ridership at the stop and stop-to-stop levels for dense and crowded bus networks. Appl Artif Intell 2016;30(09):861–85.
[4] Cham LC. Understanding bus service reliability: a practical framework using a vl/apc data. Massachusetts Institute of Technology; 2006. http://hdl.handle.net/1721.1/34381.
[5] Chien S, Ding Y, Wei C. Dynamic bus arrival time prediction with artificial neural networks. J Transp Eng 2002;128(05):429–38.
[6] Chung EH, Shalaby A. Expected time of arrival model for school bus transit using real-time global positioning system based automatic vehicle location data. J Intell Transp Syst 2007;11(04):157–67.
[7] Da Costa PRDO, Akçay A, Zhang Y, Kaymak U. Remaining useful lifetime prediction via deep domain adaptation. Reliab Eng Syst Saf 2020;195:106682.
[8] Deng Y, Di Bucchianico A, Pechenizkiy M. Controlling the accuracy and uncertainty trade-off in RUL prediction with a surrogate Wiener propagation model. Reliab Eng Syst Saf 2020;196:106727.
[9] Dragomiretskiy K, Zosso D. Variational mode decomposition. IEEE Trans Signal Process 2014;62(03):531–44.
[10] He Y, Sun C, Huang H, Jiang L, Ma M, Wang P, et al. Safety of micro-mobility: riders' Psychological factors and risky behaviours of cargo TTWs in China. Transp Res Part F 2021;80:189–202.
[11] He Y, Yang S, Chan CY, Chen L, Wu C. Visualization Analysis of Intelligent Vehicles Research Field Based on Mapping Knowledge Domain. IEEE Trans Intell Transp Syst 2021;99:1–16.
[12] Hunter T, Abbeel P, Bayen A. The path inference filter: model-based low-latency map matching of probe vehicle data. IEEE Trans Intell Transp Syst 2013;15(02):507–29.
[13] Khosravi A. Prediction intervals to account for uncertainties in travel time prediction. IEEE Trans Intell Transp Syst 2011;12(02):537–47.
[14] Kumar BA, Vanajakshi L, Subramanian SC. Bus travel time prediction using a time-space discretization approach. Transp Res Part C 2017;79:308–32.
[15] Leong W, Goh K, Hess S, Murphy P. Improving bus service reliability: the Singapore experience. Res Transp Econ 2016;59:40–9.
[16] Li R, Rose G. Incorporating uncertainty into short-term travel time predictions. Transp Res Part C 2011;19(06):1006–18.
[17] Lin WH, Zeng J. Experimental study of real-time bus arrival time prediction with GPS data. Transp Res Board 1999;1666(01):101–9.
[18] Mendes-Moreira J. Comparing state-of-the-art regression methods for long term travel time prediction. Intell Data Anal 2012;16(03):427–49.
[19] Nguyen KT, Medjaher K. A new dynamic predictive maintenance framework using deep learning for failure prognostics. Reliab Eng Syst Saf 2019;188:251–62.
[20] Pan J. A self-learning algorithm for predicting bus arrival time based on historical data model. Proc. IEEE Int Conf Cloud Comput Intell Syst 2012;3:1112–6.
[21] Pang J. Learning to predict bus arrival time from heterogeneous measurements via recurrent neural network. IEEE Trans Intell Transp Syst 2019;20(09):3283–93.
[22] Peng L, Sotelo MA, He Y, Ai Y, Li Z. Rough set based method for vehicle collision risk assessment through inferring Driver's braking actions in near-crash situations. IEEE Intell Transp Syst Mag 2019;11(2):54–69.
[23] Petersen NC, Rodrigues F, Pereira FC. Multi-output bus travel time prediction with convolutional LSTM neural network. Expert Syst Appl 2019;120:426–35.
[24] Shalaby A, Farhan A. Prediction model of bus arrival and departure times using AVL and APC data. J Public Transp 2004;7(01):41–61.
[25] Shi Z, Chehade A. A dual-LSTM framework combining change point detection and remaining useful life prediction. Reliab Eng Syst Saf 2021;205:107257.
[26] Yang H, Zhou Y, Wang Z, Wu B. A hybrid method for short-term freeway travel time prediction based on wavelet neural network and Markov chain. Canad J Civil Eng 2017;45(02):77–86.
[27] Yu H. Probabilistic prediction of bus headway using relevance vector machine regression. IEEE Trans Intell Transp Syst 2017;18(07):1772–81.
[28] Yu Z, Wood JS, Gayah VV. Using survival models to estimate bus travel times and associated uncertainties. Transp Res Part C 2017;74:366–82.
[30] Zhang M, Zhang D, Yao H, Zhang K. A probabilistic model of human error assessment for autonomous cargo ships focusing on human–autonomy collaboration. Safety Sciencei 2020;130:104838.
[31] Zhang Y, Haghani A. A gradient boosting method to improve travel time prediction. Transp Res Part C 2015;58:308–24.
[32] Zhang M, Zhang D, Goerlandt F, Yan X, Kujala P. Use of HFACS and fault tree model for collision risk factors analysis of icebreaker assistance in ice-covered waters. Safety science 2019;111:128–43.