International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

A Traffic Path Recommendation Using Time Series Based Parameter Forecasting across Origin-Destination Pair

Hitendra Shankarrao Khairnar[1], B. A. Sonkamble[2]

Submitted: 28/11/2023 **Revised**: 08/01/2024 **Accepted**: 18/01/2024

Abstract: Over the last few years, vehicular traffic path recommendation has become one of the important problems in operating road traffic networks. The shortest path recommendation across origin destination (OD) pairs is the opportunity which requires researcher's attention to extract traffic parameters like journey time, traffic speed, and traffic flow thereby improving the path recommendation for different time periods of the day. Determining conglomerate spatio-temporal correlation of traffic data to precisely predict traffic parameters is crucial for traffic path recommendation. For different time periods of a day, there is a demand for traffic situation aware spatio-temporal path recommendations. However, previous path studies focus on one-by-one traffic parameters capturing spatial dependencies ignoring temporal correlation with other traffic parameters for different time instances of the day. The paper suggests a time series-based traffic data extraction model. Selected traffic data is formulated as time series-based graph-structured (TSBG) traffic data to accommodate spatial correlations as well as temporal dependencies. The proposed model learns the edge weight predictions using average and mean square values. Simulation results demonstrate the ability to identify all possible paths and recommend optimal ones thereby affirming the effectiveness of TSBG algorithm. This paper introduces architecture for historical graph-based traffic data representation, selected traffic parameter-based path recommendation, aggregation of selected parameters that significantly improve the accuracy of extracting all possible paths and simultaneously recommending the shortest path for OD pair. The proposed method achieves better results compared to traditional forecasting methods when tested rigorously.

Keywords: *Dynamic traffic path, Time series, Graph - structured traffic data, Shortest path, Feature aggregation*

1. Introduction

Recommending the shortest path, in terms of journey time, vehicle speed, and traffic flow is a matter of high interest for an intelligent transportation system (ITS). It also has practical applications at the global level, for example assisting the traveler in deciding the path of their interest. The recommendation of the fastest route generally depends on the traffic parameters during various time periods of the day like traffic restriction of a road segment, congestion across road segments, and uncontrolled accident situations. The nature of the path recommendation system is dynamic, as there may exist multiple paths across origin destination (OD) pairs. In order to predict the cost of each of the paths at a specific time instance of a day, the task of traffic collecting parameter values during previous times instances is required. Evaluating multiple paths based on selected traffic parameters such as journey time, traffic flow, traffic density, the distance between OD pair locations, speed across adjacent road segments, etc. are important for path recommendation. Researchers have tried several techniques from time series analysis to recent deep learning algorithms for vehicular traffic parameter prediction and one of path recommendations for future time instances of a day. A newly designed recommendation system for mobility-on-demand (MOD) with dynamic vehicle routing constraints. The proposed framework was evaluated on a 7 by 7 grid network to analyze the impact of additional routing impulsion on the recommendation algorithm. Testing with the Manhattan data set with a rating of 1012 destinations reveals better performance than the benchmark of random alternatives. Service disruption of request cancellation or pickup-drop off location change limits the performance of MOD services [1]. Increasing numbers of vehicles have brought many challenges in terms of traffic jams, accidents, and frequent infrastructure maintenance activities. To overcome the limitations of self-attention mechanisms of deep time series models, a novel deep learning algorithm titled Locality-aware spatio-temporal joint Transformer elaborate spatio-temporal attention. The model was tested on three real-world data sets namely England, METR-LA, and PEMS-BAY and demonstrated that it achieves better performance than forecasting benchmarks [2]. For path planning safety problems via geometric constraints of obstacle avoidance, roadside constraints, and slide slip angle of wheels are elaborated. The concept of a certificate for distance safety and multiple object avoidance are incorporated. The proposed algorithm was to study usefulness [3]. Traffic path recommendation can be considered a modification to the

[1]Research Scholar, PICT & MKSSS Cummins College of Engineering, , Pune, Maharashtra, India hitendra.khairnar@cumminscollege.in
[2]Professor, PICT, Pune, Maharashtra, India basonkamble@pict.edu

NP-complete problem of traveling salesmen. Existing research studies neglect road traffic network integration and optimized route recommendation. Instead gives priority to stop selection, vehicle scheduling etc. The approach of a mixed integer programming scheduling scheme proposes a probing algorithm. Such an algorithm computes the time lag when recommending a path for flexible routes of OD pairs. The simulation of a real-world taxi data set shows an effective increase in the delivery ratio and reduced waiting time of passengers [4]. The accuracy of traffic parameters is important for path recommendation. The least squares support vector machine (LSSVM) has likelihood for traffic parameter prediction. However, limitations in terms of understanding meta-heuristic and slowness to achieve global optimal solutions. The experimental results of LSSVM combined with the fruit fly optimization algorithm (FOA) perform better than other single LSSVM models [5]. Journey time for OD pairs is correlated with incidents across routes and hence varies for different time periods of a day. The correlation analysis of principal component analysis (PCA) and LASSO-based time prediction models was demonstrated for the Pittsburgh region. For both prediction models, random forest prediction is promising with a root-mean-squared error of 16.6% and 17.0% each [6]. In order to test hybrid model performance, the experimental finding demonstrates that under different situations, the hybrid empirical mode decomposition - autoregressive integrated moving average (EMD–ARIMA) model performs better [7]. Most such kinds of data-driven techniques attend to the problem of traffic parameter forecasting based on the incoming and outgoing flow of vehicles. For path recommendation, there exists a recurrent neural network-based non-deterministic multi-objective algorithm, for future safety concerning criminal activities across routes [8]. Different travelers can have different priorities about the journey at different time periods of a day. Challenges for vehicular data processing and corresponding solutions based on graph optimization are significant as graph-based data processing schemes support machine learning techniques for connected vehicular data. Priorities such as fuel efficiency, wear and tear of the vehicle, road infrastructure utilization, and travel cost can lead to different route selections for OD journeys [9 -10]. In such a scenario, it is better to recommend a path based on analysis of traffic parameters present at adjacent time instances. The SAFE PATH problem is a bi-objective shortest path problem of urban navigation between source and destination location. Experimental finding justifies algorithm efficacy and practical applicability. Such recommendations may enhance persuasiveness [11].

Above mentioned techniques do not respond to multiple routes. The shortest path recommendation is important for ITS, logistics, and dispatching problems. In contrast to those elaborated techniques, the objectives of this paper are to focus on recommending the shortest path which is predicted by extracted traffic parameters namely journey time, speed across road segments, flow, and fuse the three parameters using the L2 norm as it eliminates biased recommendation. Construction of the recommended path is as follows. Starting from the origin location, the next adjacent road segment is predicted based on historical values of traffic parameters and by using a neural network for learning patterns of identified road segments and the impact of these three traffic parameters during different time periods of a day. The final path recommendation is performed using Dijkstra's shortest path algorithm.

The main contribution of the proposed work is summarized as follows:

- Modeling of traffic network as a time series-based graph (TSBG) for previous time periods.
- Edge cost in terms of traffic parameters is calculated using training of graph-based traffic networks.
- Aggregating traffic parameters using L1 and L2 norms and thereby predicting edge costs.
- In order to lessen the training and optimal computation time, we introduced a path construction mechanism using adjacent nodes and hop by hop.
- The experimental result on an open-source data set shows the proposed TSBG algorithm outran the traditional algorithms.

The following is an overview of this paper's structure: The second section offers a comprehensive review of the relevant literature for traffic parameter forecasting and traffic path recommendation. In section three, the methodology and algorithm for path recommendation. The fourth section provides results through a real-world data set. The fifth section presents the analysis of the results and addresses research questions. The paper concludes with a conclusion and future work in section six.

2. Literature Review

This section provides the review of related literature for forecasting of traffic parameter values and traffic path recommendation.

Traffic parameter forecasting: The short-term duration traffic data prediction is challenging because of its spatio-temporal nature. A survey comprising traffic parameter values prediction using state-of-the-art, deep learning methods, publicly available datasets along with their performances with respect to various methods. The classical method includes statistical, traditional machine learning methods whereas deep learning methods refer to spatio-temporal modeling. Prediction performance statistics of flow, speed, and travel time prediction for various prediction windows are listed out. Studies also highlight the limitations that data-intensive solutions are easy to implement but for non-recurrent and abnormal situations, obtaining data is challenging. Other factors which add to the limitation include knowledge fusion, long-term prediction, multi-source data, real-time predictions, model interoperability, benchmark standardization, processing high dimensional data, optimal network architecture, and prediction under perturbation. Yin et al [12]. Zhenzhen and Gao pointed out that the journey time has become dynamic and random, impacting penalty actions on traveling activities. Arrival and departure time-based path recommendation leads to a 3-parameter log-normal distribution. Beijing road network case studies demonstrate the effectiveness [13]. Duan et al. presented that the path is composed of the linking of road segments. The traffic detectors at the road intersection are useful to estimate link travel time distributions (TTDs). Three algorithms namely K-means, expectation maximization (EM) and C-shortest path are used to estimate link travel time. The experimental results prove that if 70% of the intersections are equipped with traffic detectors, the link TTDs obtained from the proposed model is excellent [14]. Zhou et al. identified the challenge of road network-wide speed prediction. The speed diagram and allocation sequence of detectors along with spatial–temporal dependencies are important. The results demonstrate that the spatial-temporal deep tensor neural networks deliver good prediction accuracy during peak as well as off-peak periods [15]. Li et al. have employed a public vehicle service (PVS), as a promising mechanism for managing and sharing large-capacity vehicles. But system efficiency was impacted by passengers waiting time and a high percentage of low-speed road utilization. Simulation of the closest meeting point algorithm shows that the passenger walking and the fast-route scheduling strategy improves the total vehicle travel distance by 34% [16]. Fang et al. aimed at fine-grained traffic prediction and a graph attention network (GAT) to predict traffic parameters at road intersections. The proposed methods outperform support vector regression (SVR), LSTM, and temporal graph convolutional network (T-GCN) for different time intervals. Root mean square error (RMSE) and mean absolute error (MAE) are used as evaluation matrices. Further modeling improvements with the help of traffic conditions such as public events and holidays need to be considered [17]. Gamboa and Borges suggested that temporal dependencies of time series lead to difficulty in analyzing different classes of problems. The reviewed papers suggest that models of deep learning can contribute a lot in the field of time series analysis and forecasting [18]. With the help of a landmark model, Zhaosheng Yang et al. present a traffic flow prediction model. Based on similarity searches of time series, mean absolute percentage error (MAPE) of the proposed method reduces to 32.8%, which is superior to the other methods under consideration [19]. Li et al. discuss an integrated study of temporal connection among the traffic time series which are observed at different days and point out advantages of principal component analysis. The review also covers data related problems of traffic time series analysis [20]. Hu et al. address the issue of complex problem of path planning in terrain areas. A technique of the Voronoi diagram is used for path planning. As an advancement, the author also suggests extension in the form of velocity-based planning [21]. Isinkaye et al. discussed the importance of the recommendation system, as there exist new opportunities for retrieving traffic information. Authors explained the characteristics of traditional recommendation techniques, strengths, and challenges with diverse kinds of hybridization strategies. The highlights of the paper includes, the importance of various feedback for information collection, recommendation techniques, and evaluation metrics of recommendation algorithms [22]. Wang et al. suggested that the collaborative filtering approach is commonly used by many recommendation systems. A recent appealing method of collaborative topic regression (CTR) is based on learning from two sources of information [23]. Zhao et al. noted the observation that because of the cost difference, travelers may change their routes dynamically. A method of mapping dynamic routing behavior to day-to-day assignment problems is incorporated. It has been observed that the traveler's estimated and expected costs vary dynamically according to rerouting weights. The findings of the experiments can be extended to the evolution patterns of transportation [24].

Traffic path recommendation: Bohan et al. suggested that for supply chain management, a conglomerate road network is a challenge for a path recommendation. Proposed prediction of optimized route path recommendation based on trusted models considers historical, current, and predicted traffic conditions [28]. Xu et al. implemented representation of road traffic formulation to collect location-based relations of traffic parameters at different time instances. The discriminating features of traffic data are extracted using graph convolutional networks. This approach is about small-scale space, time, and feature filtering with the help of tucker decomposition to reduce computational workload [29].

Papadopoulos et al. proposed an approach to improve the path recommendation. Customized routing instructions are provided based on a person's preferences and ensure that the recommendation satisfies the budget balance of the total driving cost. Maximum likelihood estimation-based clusters are used to separate drivers into various clusters [30]. Jiexia Ye et al. has pointed out that in the last couple of years, different deep learning architectures consisting of deep learning techniques have been proposed to solve spatial-temporal dependencies among traffic parameters. To utilize the traffic network efficiently, it's better to formulate the same with mathematical graphs. Guidelines about formulating graphs from different traffic data sets along with shared deep learning techniques have been presented. Future directions in terms of applications, techniques, and external factors are also mentioned [31].

However, most of the OD path recommendation models tend to avoid the topological formation of vehicular traffic networks. Many researchers modeled vehicular traffic formulation as a passive graph, which fails to collect the dynamic flavor. Such an act limits the traffic prediction performance. To address this issue TSBG representation is proposed. As there exists road segment interconnection of citywide transportation networks, an effective path recommendation model should consider traffic parameters of earlier time duration associated with adjacent road segments. TGSB path recommendation algorithms explore routes between vertices, starting at the origin and traversing through adjacency relationships, hop by hop until the destination has been reached. First, traffic data collection locations have been identified. Based on these locations, a road traffic network graph is then constructed, where nodes are traffic data collection locations and edges are road segments across those locations. Inspired by graph-structured traffic data representation, two different types of edge weights are predicted using L1 and L2 regularization of traffic parameters, the average and the mean square values of traffic parameters respectively. State-of-the-art path algorithms are used for multiple traffic path identification. For various periods, path recommendation across OD pairs is formulated as a ranking problem.

3. Methodology

In this section, we introduce the path recommendation problem and algorithm of our model.

3.1 Problem Definition

The path recommendation system aims to extract multiple paths across an OD pair by predicting future traffic data (speed, journey time, flow) based on previous period observations. We define a time-series based weighted representation of the road network. G = (V, E, W), where V is traffic data collection locations. E is a set of edges connecting to adjacent locations. W ∈ R N X N is a weighted adjacency matrix of G. Edge weight is predicted based on the average (L1 norm) and the mean square (L2 norm) of extracted traffic parameters. As in Equation 1, edge weight prediction aims to learn prediction function f for predicting the values for Tp future time Ý ∈ R, Tp X N X W form previously known periods ∈ R Tp X N X W and Graph G

$$\left[X_1, X_2, \ldots . X_{Th} : G \right] \rightarrow f(.)\left[Y_{Th+1,} \ldots Y_{Th+Tp}\right] \quad (1)$$

Vehicular traffic path recommendation at a particular time instance of a day is a specific problem of time series. The collection of traffic parameters for every 15 minutes, leads to the sequence of traffic parameter data which is represented by a graph. a TSBG model selects a traffic parameter based on forward feature selection and predicts routes based on each selected parameter. The model further evaluates shortest path recommendation using edge weights based on the average (L1 norm) and the mean square (L2 norm) of selected traffic parameters. To recommend an optimal path at a particular time instance, a TSBG model is proposed as in *Figure 1*.

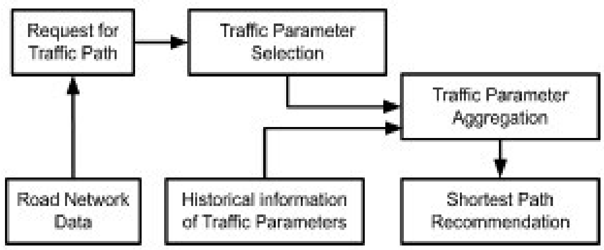
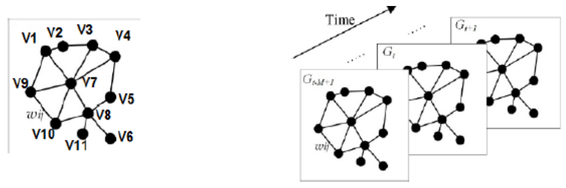


Fig 1. Path recommendation model framework of TSBG

3.2 Historical Graph based information

Representation of selected traffic features using graph-structured formulation helped to learn location-based and time-front properties of traffic data. This in turn leads to identifying multiple paths across OD pairs and recommending the shortest path with the support of a standard algorithm. Forecasting of traffic parameter values is a location-aware services problem. Based on the training of previous few time intervals traffic data, prediction of subsequent time intervals data is possible using L1 and L2 regularization. The model proposes a road network formulation using a graph. Vehicular traffic data collection locations are constructed as nodes of a graph and edge models road segments connecting nodes. Edges are constructed if there exists a connection between pairs of nodes.

Figure 2 (a) represents a simple graph-structured representation of the road network. Let $G_t \in R^n$ is an observation vector of the number of locations. For a specific time instance t, each element of the observation vector records the historical traffic parameter for a location. G_t is adjacent to other data collection locations. Therefore, the traffic parameters value of the road segment is represented as non-directed graph edge weight W_{ij}, as shown in *Figure 2 (b).* $G_t = (V_t, E_t, W)$, is an observation vector of traffic data collection locations at time instant t, E is a set of edges to connect adjacent locations; W is the weighted matrix for G_t [27].



(a) (b)

Fig 2. (a) Simple Graph structured representation of road network (b) An observation vector

3.3 Traffic parameter selection

For various periods of a day, for the TSBG model, the information about the OD pair is requested. Three fundamental traffic parameters speed, journey time, and traffic flow across various nodes of OD pair are selected from an open-source data set. Traffic data collection records traffic details over stipulated time intervals. Selected features should be processed for feature aggregation. As values of parameters vary for different times, corresponding edge weights W_{ij} of a graph also vary.

3.4 Traffic parameter aggregation

Edge weights are predicted using L1 and L2 norms of traffic parameters over the previous few time instances. The difference between the predicted traffic parameter value and corresponding ground truth values should be minimal. For each of the selected features, there exists a time series data. The set of selected parameters describes the nature of a traffic system. For example, flow at instant t_n, speed of vehicle, and journey time required to traverse across road segments at that time instant t_n.

The set of time steps describes discrete values representing finite time intervals. For example, 15 minutes, 96 instances for 24 hours of a day [26]. One way to aggregate parameter time series is to merge multiple times series. Such an approach is suitable for spatio-temporal aggregation [25]. The proposed TSBG model uses averaging and the mean square of traffic parameters at adjacent time instances and thereby aggregation of traffic parameters. Traffic parameters of a road segment are affected by recent, daily, and weekly traffic patterns whereas the degree of influence may be different. Therefore, for aggregation of traffic parameters, the L1 norm of Equation (2) is used, which is the sum of absolute traffic parameter values. Edge weight is calculated as follows

$$\left|W_{ij}\right| = |JT| + |Flow| + |Speed| \quad (2)$$

The L1 norm gives edge weight using an average of traffic parameters. As another method of traffic parameter aggregation, for the same dataset, the L2 norm as shown in Equation (3) is used to offset bias of all of the traffic parameter values.

$$|Wij| = \sqrt{(JT)^2 + (Flow)^2 + (Speed)^2} \quad (3)$$

3.5 Path recommendation

There exist multiple paths for OD pairs. All the nodes of the graph and corresponding edges are processed hop by hop to compute multiple paths of the OD pair. Suppose a TSBG, $\hat{G} = \{G^{(1)}, G^{(2)} \ldots G^{(T)}\}$ where $G^{(t)} = (V^{(t)}, E^{(t)})$, t = 1,2,...T is a graph-structured representation of a road network. Traffic parameter information based on previous single period may not be sufficient for future traffic parameter value prediction and path recommendation. There is a need to analyze a larger duration traffic parameter data to predict edge weights across OD pair and time series structure. Let's consider two nodes 'i' and 'j' in a route. There exist multiple edges between nodes 'i' and 'j' along with traffic data collection nodes. Each edge has its own journey time, speed, traffic flow, and distance as shown in *Figure 3.*

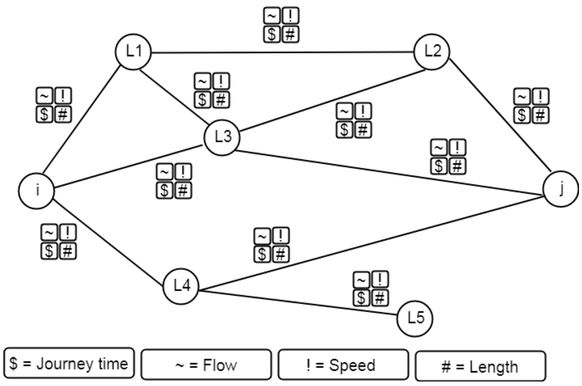


Fig 3. Predicted edge cost of different traffic parameters across edges of two nodes 'i' and 'j'

For example, A5 - A45 is an OD pair of a data set. There exist multiple paths going through different data-capturing locations. For each of the adjacent locations traffic parameters namely speed, journey time, and traffic flow are extracted along with distance. Edge weight as assigned as per L2 norms of selected parameters. The nodes of the recommended shortest path are A5 - A453 - A50 - A46 - A45.

Algorithm 1 shows TSBG formulation. Graphs were processed to calculate the distance of reachable nodes from a source node.

Algorithm 1: Time Series Based Graph (TSBG) formulation

Input Data: Time series based traffic data, time instance, data collection location, M previous time instances

Result: TSBG representing spatial and time instance context at data collection location

1. i ← 1 // Current time instance

2. while (i < M) // ∀ previous training time instances

3. Identify each edge (u,v) of the graph at a specific time instance of data collection location,

∀(u,v)ϵE,||Wuv|| = Sqrt (JT2+Speed2+Flow2+Length2)

// Calculate edge weight based on predicted traffic data specific time instance

4. i ← i + 1

5. end while // Edge weights of previous time instances for training

Algorithm 2 describes the reachable node computation starting from the source location. For calculating hop-by-hop reachable nodes, a queue data structure is used. enqueue(x): operation puts a traffic information collection location 'x' at the end of the queue and dequeue (x): returns the first data collection location of the queue. For each of the data collection locations, adjacent data collection locations are identified and inserted in a queue. Traffic parameters are selected across edges for time instances. Auto regressive integrated moving average (ARMA), vector auto-regression, (VAR), support vector regression (SVR), bayesian and k-nearest neighbor (KNN) bench-marking methods along with Dijkstra's shortest path technique are used to compare the performance of recommendation.

Algorithm 2: Training procedure and multiple path computation of TSBG

Input Data: Time series based traffic data related graph G (V,E), time instance, OD pair

Result: Return Optimal path across OD pair

Data: ∀ nodes t, reachable from origin, distance[t] ← the weight of the smallest path from origin to node t. Otherwise, distance[t] ← ∞, ∀ nodes not reachable from origin.

1. Path cost = 0, distance[origin] = 0, ∀ V ∈ Gt not adjacent to the origin, distance[vi] = ∞ // Initialization

2. Q.enqueue (origin) // Initialize queue, add adjacent vertices of Origin

3. While (Q ≠ ∅) do // Check for adjacency

4. u ← Q.dequeue() // Adjacent data collection location

5. ∀ (u,v) ∈ E do // Identify all adjacent vertices of the current vertex

6. Q.enqueue(v) // Add adjacent data collection locations of v

7. if distance[v] = ∞ then distance[vi] ← distance[u] + ||Wuv|| // Here ||Wuv|| calculated using L2 norm, average and mean square value of traffic parameters

8. Repeat for all adjacent vertices of u // Edge weights ∀ adjacent vertices

9. else

10. distance[vi]←Minimum (distance[vi],distance[u] + ||Wuv||) // If required, calculate modified distance

11. Compute distance for processing of ∀ vertices and ∀ edges belonging to graph G(V,E) // Compute all edges weights

12. Calculate all possible paths across OD pair // Multiple paths may exist across OD pair

13. Return Optimal path cost across OD pair = MINpath∈OD(Path1, Path2, ..., nth Path) for specific time instance ti // Minimum cost

A significant addition of the paper is to represent vehicular traffic data across traffic networks as graph-structured traffic data, a unique representation of spatial and temporal context distribution. This approach provides interpretative inference over changing graph elements (time instances, vertices, edge weights). To achieve this goal, our framework of *Figure 1* needs to be capable of learning traffic parameters for context sampling (e.g. training window of length M, data collection time-frequency) to atomically train on different graphs. Next, to obtain a suitable representation of the graph-structured traffic data, we jointly model the spatial and temporal context. Finally, the end-user can investigate graph context distribution by aggregating the traffic parameter values for edge weight calculations and recommending the shortest path.

4. Result Analysis

To analyze the performance of traffic path recommendation, an experiment on open source traffic data set is carried out and compared with standard methods.

4.1 Data Set

We evaluate TSBG on England traffic data set which records traffic parameters of England highway from 1st January 2015 to 31st December 2015. The data set aggregates traffic parameters observation into 15-minute windows. 70% of the data set is used for training, 10% for validation, and 20% for testing. The distribution of sensors for the data set is as shown in *Figure 4*.

Fig 4. Distribution of Sensors for data set [26]

4.2 Experimental settings

Training of 180 minutes as the historical time window, which is nothing but the observed traffic parameter over the 15-minutes interval. These records were used to construct graph-structured traffic data, as shown in *Figure 2 (b)*, and to forecast traffic parameter values for future 15-minute time intervals. An experimental setup includes implementation with Python 3.6, and TensorFlow 1.9.0 on the Linux platform. Intel Core i7-7700HQ CPU with 16 GB RAM, GeForce GTX 1070/PCle/SSE2 of 6 GB RAM.

From a data set an OD-pair A6006-A61 link referenced as UKHN8135, having 16 data collection locations across it. Every node of the road network graph contains 96 data points per day.

4.3 Baselines

We compared our TSBG model with those of five well-known baseline models. A brief introduction to these is shown in Table 1.

Table 1 Brief introduction to the baseline models

Name	Description
ARMA	Forecasting model in which the methods of auto regression (AR) analysis and moving average (MA) are both applied to time-series traffic data
VAR	Vector auto-regression, to capture the pairwise relationship among multiple time series of traffic data for vehicular traffic networks
SVR	Support vector regression to iteration wise perform multi step prediction
Baysian	For feature selection and the distribution of the unobserved (future) data given the observed data
KNN	Estimating the likelihood that an edge will become a member of shortest path group or another based on what group the data points nearest to it belong to

4.4 Model Training

To train the TSBG model, MAE is used as a loss function. As shown in Equation (4) where 'n' is the number of data points, y(i) is the ith measurement, and y ̃(i) is its corresponding prediction. Traffic parameter values of different time instances are divided into a training set, a validating, and a testing set.

$$Loss = MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - x_i| \quad (4)$$

4.5 Evaluation metric

To measure and evaluate the accuracy of the performance for all experiments on the data set, RMSE, MAE and MAPE as in Equations (4) - (6) are used.

$$RMSE = \sqrt{1/n \sum_{t=1}^{n} (\hat{y}_i - y_i)^2} \quad (5)$$

Where n is the number of data points, y_i is the ith measurement and $\hat{y}_i$ is its corresponding predicion.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{A_t - F_t}{A_t}\right| \quad (6)$$

Where n is the number of times the summation iteration happens. At is the actual value of the traffic parameter and Ft is the predicted value of traffic parameter.

4.6 Experimental Results

Figure 5 illustrates a representation of graph-structured traffic data for learning spatial and temporal property across OD pair A181-A135 at time instance 25 (6:15 am) of a day. A node represents vehicular traffic data collection locations and edges are road segments connecting those nodes. Based on the training of a single traffic parameter, average of selected traffic parameters as in Equation (2) and mean squares of selected traffic parameters Equation (3) , TSBG predicts traffic parameter values for subsequent time intervals. Extraction of multiple paths for OD pairs using brute force approach and Dijkstra's algorithm is used to recommend the shortest path. The edge cost of the recommended shortest path may vary depending on traffic data of specific period, thereby demonstrating the dynamic path recommendation ability of TSBG. Recommended shortest path edges for OD pair A181-A135 are A181, A19, A1130, A66, A135.

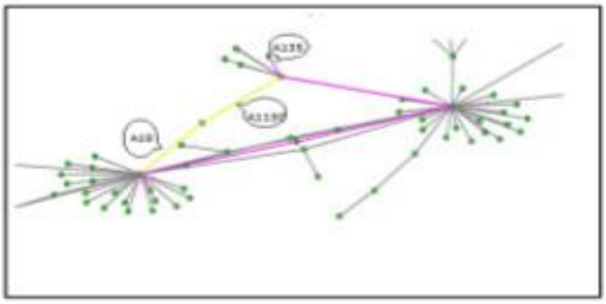


Fig 5. OD pair A181-A135 at time instance 25

Figure 6 illustrates a representation of graph-structured traffic data for OD pair A181 - A135 for time instance 50 of a day. Recommended edges of the shortest path are A181, A1068, A1, A66, and A135 demonstrating the dynamic path recommendation ability of TSBG.

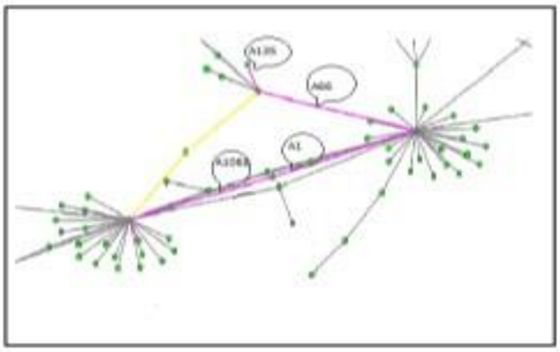


Fig 6. OD pair A181-A135 at time instance 50

5. Discussion

For baselines, if their accuracy is not known for a data set, execute the corresponding codes for selected traffic parameters and recommended configuration. This section aims to address the following questions.

Q1. How does the TSBG framework perform as compared to various standard algorithms?

Q2. How do different parameters affect the results of TSBG?

Q3. How efficient is TSBG for parameter prediction?

Q4. What is the influence of forecasting time frames in TSBG?

Q5. Can TSBG provide interpretation ability concerning spatial and temporal dimensions?

5.1 Performance Comparison (Q1)

We list the evaluation results of standard methods in Table 2. In general, the experience is that TSBG outperforms baseline techniques for different time window predictions. Along with that, we have the following observations about experimental results. Firstly, a good representation ability of Bayesian and KNN on non-linear traffic data is compared with statistical techniques of ARMA, VAR, and SVR. The results of TSBG further show the robust generalization performance and effectiveness of spatial-temporal correlation in Table 2.

5.2 Ablation Study (Q2)

We tested TSGB to verify the effectiveness of path cost and the edges prediction with individually forecasted parameter values namely traffic flow, speed, and journey time. We also study the effect of averaging and weight square mean for path cost and edge prediction for path recommendation. Table 2 - 7 shows the shortest recommended path edges, shortest path cost, and number of paths across OD pairs based on the selected feature. The performance of a single parameter based recommendation indicates that just one parameter is not sufficient for an optimal recommendation. Thus, Weight square mean based (L2 norm) edge cost prediction proves the optimal path.

5.3 Computation Needs (Q3)

The computational demand of TSGB for training time, inference time, and memory usage with baselines is compared. With the help of overlapping time windows of the training period, TSGB achieves better time and memory utilization with baseline algorithms.

5.4 Effect of time forecasting frame (Q4)

Concerning Table 2, for prediction assessment of the proposed method, we observed that for small forecasting horizons of 15 min, MAE and MAPE were small. As the prediction horizon increases, MAE and MAPE also increase.

5.5 Parameter relations (Q5)

Experimental results indicate that our model can better dynamically relate relations of traffic data. For example speed and journey time, flow and speed, flow and journey time, etc. The relation of selected parameters also depends on the sparse or dense placement of sensors to collect traffic data. For sparsely located sensors traffic flow is more fluctuating than the traffic speed resulting in a larger standard deviation.

In order to verify whether the TSBG model could capture traffic parameters from the data set, we compare TSBG with ARMA, VAR, SVR, Bayesian, and KNN. Comparison involves the prediction of individual feature-based as well as mean and square mean-based traffic path recommendation for 15 minutes, 30 minutes, and 45 minutes.

Prediction capability: For 15-minutes predictions TSBG reported MAPE of 20.92%, for 30 minutes MAPE of 26.10% and for 45 minutes 32.28% indicating that TSBG can capture correlation with earlier time instances.

Prediction ability: As shown in table 2, TSBG can handle temporal correlation well. Compared to ARMA, VAR, SVR, Bayesian, and KNN for 15-minutes, the RMSE of TSBG is 52.77, for 30 minutes RMSE is 60.53 and for 45 minutes 70.81. The main reason for ARMA's worse prediction accuracy is that it is difficult to deal with long series of non-stationary traffic data. The RMSE of various models is as shown in Table 2.

Traffic parameter forecasting results show that the error and prediction accuracy of TSBG change little with time, indicating that the proposed model has certain stability. No matter how much a time frame for a recommendation will be, the model can obtain the best prediction results. Therefore, TSBG can be used not only for short-term traffic path recommendation but also for medium-term and long-term traffic path recommendation.

Table 2 Traffic parameter forecasting performance on the data set

Algorithm	**15 minutes**			**30 minutes**			**45 minutes**		
	MAE	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)
ARMA	60.23	85.79	42.15	92.17	155.39	75.68	142.59	225.19	85.45
VAR	50.14	78.72	36.46	82.66	122.82	60.57	105.21	150.72	83.10
SVR	54.42	85.88	53.23	91.02	152.44	70.12	139.35	223.89	74.75
Bayesian	34.87	59.97	25.14	41.02	71.92	30.10	46.45	83.21	34.59
KNN	34.11	59.13	25.92	48.30	83.83	34.18	65.25	117.96	42.02
TSBG	**29.16**	**52.77**	**20.92**	**33.20**	**60.53**	**26.10**	**38.44**	**70.81**	**32.28**

For various OD pairs, traffic flow-based recommendations are shown in Table 3. For example, for OD pair A181 - A135 there exist 6 paths, and the recommended path cost via A1068, A1, and A66 edges is 181.50 units. We have tested TSBG with 10 different OD pairs. Other pairs and related cost of the recommended shortest path is also shown in Table 3.

Table 3 Traffic flow based recommended path for different OD pairs

Origin	**Destination**	**Shortest recommended path edges**	**Shortest path cost**	**Number of non dominant paths**
A181	A135	A181, A1068, A1, A66, A135	181.500	6
A386	A1130	A386, A38, A511, A52, A1,A1068, A19, A1130	288.500	1260
A5	A45	A5, A38, A50, A46, A45	198.630	426
A1166	A5094	A1166, A63, A1079, A64, A19,A1068, A1, A66, A595, A5094	258.250	12
A55	A135	A55, A51, A5, A453, A52,A1, A66, A135	334.380	2334
A31	A66	A31, A3, A423, A45, A46,A1, A66	324.500	1296
M23J11	A591	M23J11, A23, A272, A3, A423,A45, A46, A6, A590, A591	591.000	217
A388	A591	A388, A36, A303, A34, A500,A50, A6, A590, A591	364.300	217
A1033	A597	A1033, A63, A1079, A64, A19, A1068, A1, A66, A595, A597	270.750	12
A6055	A1018	A6005, A52, A1, A1068, A19, A1018	207.000	636

For various OD pairs, traffic speed-based recommendations are as shown in Table 4. For example, for OD pair A1166 - A5094 there exist 12 paths, and the recommended path cost via A1166, A63, A1079, A64, A19, A1130, A66, A595, and A5094 edges is 686.680 units. Other pairs and related cost of the recommended shortest path is also shown in Table 4.

Table 4 Traffic Speed based recommended path for different OD pairs

Origin	Destination	Shortest recommended path edges	Shortest path cost	Number of non dominant paths
A181	A135	A181, A19, A1130, A66, A135	405.340	6
A386	A1130	A386, A38, A511, A52, A1, A1068, A19, A1130	539.440	1260
A5	A45	A5, A453, A50, A46, A45	374.080	426
A1166	A5094	A1166, A63, A1079, A64, A19, A1130, A66, A595, A5094	686.680	12
A55	A135	A55, A51, A5, A453, A52, A1, A66, A135	646.920	2334
A31	A66	A31, A3, A423, A45, A46, A1, A66	469.620	1296
M23J11	A591	M23J11, A23, A272, A3, A423, A45, A46, A6, A590, A591	818.26	217
A388	A591	A388, A36, A303, A34, A500, A50, A6, A590, A591	710.470	217
A1033	A597	A1033, A63, A1079, A64, A19, A1130, A66, A595, A597	640.370	12
A6055	A1018	A6005, A52, A1, A184, A19, A1018	423.620	636

For various OD pairs, traffic journey time-based recommendations are as shown in Table 5. For example, for OD pair A181 - A135 there exist 6 paths, and the recommended path cost via A19, A1130, and A66 edges is 349.310 units. Other pairs and related cost of the recommended shortest path is also shown in Table 5.

Table 5 Traffic journey time based recommended path for different OD pairs

Origin	Destination	Shortest recommended path edges	Shortest path cost	Number of non dominant paths
A181	A135	A181, A19, A1130, A66, A135	349.310	6
A386	A1130	A386, A38, A511, A52, A1, A184, A19, A1130	542.330	1260
A5	A45	A5, A453, A52, A500, A50, A46, A45	439.650	426
A1166	A5094	A1166, A63, A1079, A64, A19,A1130, A66, A595, A5094	1038.850	12
A55	A135	A55, A51, A5, A453, A52,A1, A66, A135	630.449	2334
A31	A66	A31, A3, A423, A45, A46,A50,A500,A52, A1, A66	900.650	1296
M23J11	A591	M23J11, A23, A272, A3, A423,A45, A46, A6, A590, A591	1313.180	217
A388	A591	A388, A36, A303, A34, A500,A50, A6, A590, A591	2871.979	217
A1033	A597	A1033, A63, A1079, A64, A19, A1130, A66, A595, A597	797.540	12
A6055	A1018	A6005, A52, A1, A184, A19, A1018	453.549	636

For various OD pairs, weight square mean-based recommendations are as shown in Table 6. For example, for OD pair A181 - A135 there exist 6 paths, and the recommended path cost via A19, A1130, A66 edges is 61.220 units. The advantage of a square mean of traffic parameters is to restrict the biasing of any one traffic parameter and over-fitting of edges for the recommended path.

Table 6 Weight square mean based recommended path for different OD pairs

Origin	**Destination**	**Shortest recommended path edges**	**Shortest path cost**	**Number of non dominant paths**
A181	A135	A181, A19, A1130, A66, A135	61.220	6
A386	A1130	A386, A38, A511, A52, A1, A66, A1130	92.508	1260
A5	A45	A5, A453, A50, A46, A45	66.700	426
A1166	A5094	A1166, A63, A1079, A64, A19, A1130, A66, A595, A5094	126.353	12
A55	A135	A55, A51, A5, A453, A52, A1, A66, A135	106.253	2334
A31	A66	A31, A3, A423, A45, A46, A1, A66	108.104	1296
M23J11	A591	M23J11, A23, A272, A3, A423,A45, A46, A6, A590, A591	151.415	217
A388	A591	A388, A36, A303, A34, A500, A50, A6, A590, A591	165.363	217
A1033	A597	A1033, A63, A1079, A64, A19, A1130, A66, A595, A597	116.659	12
A6055	A1018	A6005, A52, A1, A184, A19, A1018	79.130	636

For various OD pairs, weight mean-based recommendations are shown in Table 7. For example, for OD pair A181 - A135 there exist 6 paths, and recommended path cost via A19, A1130, and A66 edges is 238.442 units.

Table 7 Weight mean based recommended path for different OD pairs

Origin	**Destination**	**Shortest recommended path edges**	**Shortest path cost**	**Number of non dominant paths**
A181	A135	A181, A19, A1130, A66, A135	238.442	6
A386	A1130	A386, A38, A511, A52, A1, A66, A1130	362.00	1260
A5	A45	A5, A453, A50, A46, A45	287.910	426
A1166	A5094	A1166, A63, A1079, A64, A19, A1068, A1, A66, A595, A5094	504.319	12
A55	A135	A55, A51, A5, A453, A52,A1, A66, A135	406.832	2334
A31	A66	A31, A3, A423, A45, A46, A1, A66	533.694	1296
M23J11	A591	M23J11, A23, A272, A3, A423, A45, A46, A6, A590, A591	689.549	217
A388	A591	A388, A36, A303, A34, A500, A50, A6, A590, A591	1003.280	217
A1033	A597	A1033, A63, A1079, A64, A19, A1130, A66, A595, A597	433.522	12
A6055	A1018	A6005, A52, A1, A184, A19, A1018	315.697	636

Figure 7 illustrates traffic path cost based on different parameters of traffic along with the mean and square mean of the same parameters. The horizontal axis represents the various order pairs and the vertical axis represents the optimal cost of the recommended shortest path for respective order pairs using parameters under consideration. The selection of parameters determines the forecasting effect for the recommendation. It has been observed that path recommendations based on traffic parameter aggregations are more cost-effective than individual traffic parameter-based recommendations.

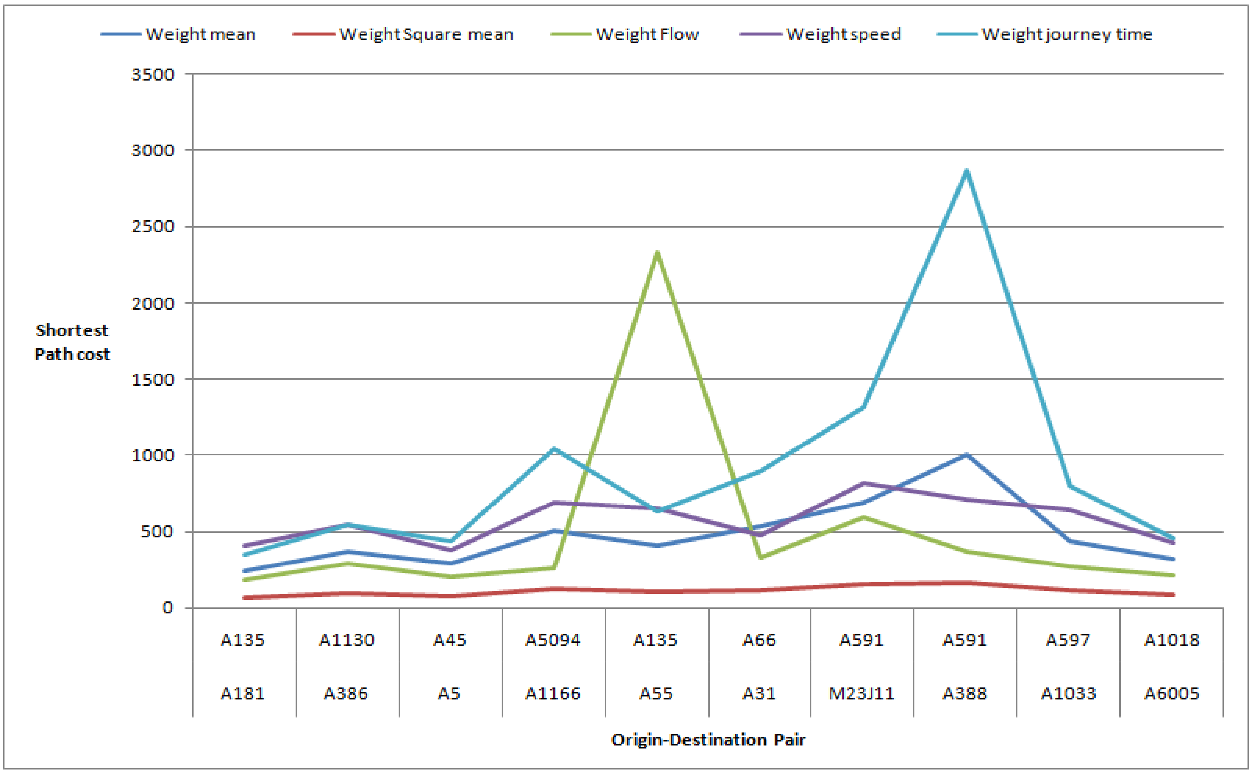


Fig 7. Forecasted shortest path cost for selected traffic parameters along with mean and square mean weight

6. Conclusion and Future Scope

In this paper, the contribution is about representing traffic data using a time series graph. Edge weights are predicted based on previous time instances of selected traffic parameters. Dijkstra's algorithm is used for the shortest path recommendation. TSBG's approach of modelling vehicular traffic network as a graph and edge weights prediction using traffic flow, speed, journey time, mean of these three traffic parameters, and mean square value of three selected parameters, is the first one to the best of our knowledge. To reduce the dimensions of records processing, and to exploit pattern likeliness among adjacent time instances, we have used a 15-minutes traffic data set. The focus of the recommendation is for specific time instances, extracting a relevant list of paths across OD pairs, and comparing the same with ground truth baseline methods. The extracted list of OD pair paths is validated with the help of weight bounds on paths. A path having minimum cost is recommended and other paths are ranked based on increasing path cost. The proposed TSBG method could be adequate to handle the congestion problem and the operational level utilization of the road network. Further scope of exploring different traffic features and algorithms for aggregation to maintain a portfolio of routes for traffic path recommendation across OD pairs. A probable set of indicators for sustainable transportation-related activities of proposed work include economical optimization of traffic congestion, infrastructure costs, paths with minimum accident spots. Further scope of work can be enhanced by considering the environmental aspects like a recommendation of a path with less noise and air pollution.

References:

[1] Gyugeun Yoon, Joseph Y. J. Chow, Assel Dmitriyeva, and Daniel Fay. Effect of routing constraints on learning efficiency of destination recommender systems in Mobility-on-Demand Services. IEEE Transactions on Intelligent Transportation Systems. 2022; 23(5): 4021-4036.

[2] Yuchen Fang, Fang Zhao, Yanjun Qin, Haiyong Luo, and Chenxing Wang. Learning All Dynamics: Traffic Forecasting via Locality-Aware Spatio-Temporal Joint Transformer. IEEE Transactions on Intelligent Transportation Systems.2022; 23(12): 23433-23446.

[3] Yushu Yu, Dan Shan, Ola Benderius, Christian Berger, and Yue Kang. Formally Robust and Safe Trajectory

Planning and Tracking for Autonomous Vehicles. IEEE Transactions on Intelligent Transportation Systems. 2022; 23(12):22971-22987.

[4] Yongxuan Lai , Fan Yang , Ge Meng, and Wei Lu. Data-Driven Flexible Vehicle Scheduling and Route Optimization. IEEE Transactions on Intelligent Transportation Systems. 2022;23(12):23099-23111.

[5] Y. Cong, J. Wang and X. Li. Traffic flow forecasting by a least squares support vector machine with a fruit fly optimization algorithm. Procedia Eng.2016; 137:59 - 68.

[6] S. Yang and S. Qian. Understanding and predicting roadway travel time with spatiotemporal features of network traffic flow, weather conditions and incidents. Transportation Research Board 97th Annual Meeting Proc 2018 (pp 1-7).

[7] Haizhong Wang, Lu Liu,Shangjia Dong,Zhen Qian and Heng Wei. A novel work zone short-term vehicle-type specific traffic speed prediction model through the hybrid EMD-ARIMA framework. Transportmetrica B, Transport Dynamics. 2016;4(3): 159 - 186.

[8] A. M. de Souza, T. Braun, L. C. Botega, L. A. Villas and A. A. F. Loureiro.Safe and Sound: Driver Safety-Aware Vehicle Re-Routing based on Spatiotemporal Information. IEEE Trans on Intelligent Transportation Systems. 2020; 21(9): 3973 - 3989.

[9] A.E. Taha and N. AbuAli. Route planning considerations for autonomous vehicles. IEEE Communication. 2018 (pp. 78 - 84).

[10] Zhigao Zheng and Ali Kashif Bashir. Graph-Enabled Intelligent Vehicular Network Data Processing. IEEE Transactions on Intelligent Transportation Systems. 2022; 23(5): 4726 - 4735.

[11] Esther Galbrun, Konstantinos Pelechrinis and Evimaria Terzi. Urban navigation beyond the shortest route: The case of safe paths. Information Systems. 2016; 57(C): 160 - 171.

[12] Xueyan Yin, Genze Wu, Jinze Wei, Yanming Shen, Heng Qi, and Baocai Yin. Deep Learning on Traffic Prediction: Methods, Analysis, and Future Directions. IEEE Transactions on Intelligent Transportation Systems. 2022; 23(6): 4927 - 4943.

[13] Zhenzhen, and Ziyou Gao. Finding Reliable Paths Considering the earliest Arrival Time and the Latest Departure Time With 3-parameter Log normal Travel Times. IEEE Transactions on Vehicular Systems. 2020; 69(10): 10457 - 10468.

[14] P. Duan, G. Mao, J. Kang and B. Huang. Estimation of Link Travel Time distribution with limited Traffic Detectors. IEEE Transactions on Intelligent Transportation Systems.2020; 21(9): 3730 - 3743.

[15] Lingxiao Zhou, Shuaichao Zhang, Jingru Yu and Xiqun Chen. Spatial-Temporal Deep Tensor Neural Networks for Large-Scale Urban Network Speed Prediction. IEEE Transactions on Intelligent Transportation Systems.2020; 21(9): 3718 - 3729.

[16] N. Li, L. Kong, W. Shu and M. -Y. Wu. Benefits of Short-Distance Walking and Fast-Route Scheduling in Public Vehicle Service. IEEE Transactions on Intelligent Transportation Systems 2020; 21(9):3706 - 3717.

[17] Mengyuan Fang, Luliang Tang, Xue Yang, Yang Chen, Chaokui Li, and Qingquan L. FTPG: A FineGrained Traffic Prediction Method With Graph Attention Network Using Big Trace Data. IEEE Transactions on Intelligent Transportation Systems. 2022; 23(6): 5163 - 5175.

[18] Gamboa and John Cristian Borges. Deep Learning for Time-Series Analysis. arXiv preprint arXiv:1701.01887. 2017.

[19] Zhaosheng Yang, Qichun Bing, Ciyun Lin, Nan Yang and Duo Mei. Research on short-term traffic flow prediction method based on similarity search of time series. Mathematical Problems in Engineering, 2014;14(1):1-8.

[20] L. Li, X. Su, Y. Zhang, Y. Lin and Z. Li. Trend Modeling for Traffic Time Series Analysis: An Integrated Study. IEEE Transactions on Intelligent Transportation Systems. 2015; 16(6) 6: 3430 - 3439.

[21] Jiaming Hu, Yuhui Hu, Chao Lu, Jianwei Gong, and Huiyan Chen. Integrated Path Planning for Unmanned Differential Steering Vehicles in Off-Road Environment With 3D Terrains and Obstacles. IEEE Transactions on Intelligent Transportation Systems. 2022; 23(6):5562 - 5572.

[22] F.O. Isinkaye , Y.O. Folajimi and B.A. Ojokoh. Recommendation systems: Principles, methods and evaluation. Egyptian Informatics Journal. 2015;16(3): 261 - 273. 2015.

[23] Hao Wang, Naiyan Wang and Dit-Yan Yeung. Collaborative deep learning for recommender systems. 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 2015(pp. 1235-1244).

[24] X. Zhao, C. Wan, H. Sun, D. Xie and Z. Gao. Dynamic Rerouting Behavior and its impact on Dynamic Traffic Patterns. IEEE Transactions on Intelligent Transportation Systems. 2017. 18(10): 2763 - 2778.

[25] Maximilian Hoffmann, Leander Kotzur, Detlef Stolten

and Martin Robinius. A Review on Time Series Aggregation Methods for Energy System Models. Energies. 2020(pp.1 - 13).

[26] H. England, “Highways agency network journey time and traffic flow data,” Tech. Rep. [Online]. Available: https://data.gov.uk/dataset/dc18f7d5-2669-490f-b2b5-77f27ec133ad/highways-agencynetworkjourney-time-and-traffic-flow-data

[27] Yong Han, Shukang Wang, Yibin Ren, Cheng Wang, Peng gao and GE Chen. Predicting Station-Level Short-Term Passenger Flow in a Citywide Metro Network Using Spatiotemporal Graph Convolutional Neural Networks. International Journal of Geo-Information. 2019; 243(8):1-24.

[28] Bohan Li, Tianlun Dai, Weitong Chen, Xinyang Song, Yalei Zang, Zhelong Huang, Qinyong Lin, and Ken Cai. T-PORP: A Trusted Parallel Route Planning Model on Dynamic Road Networks. IEEE Transactions on Intelligent Transportation Systems. 2023; 24(1):1238-1250.

[29] Xuran Xu, Tong Zhang, Chunyan Xu, Zhen Cui and Jian Yang. Spatial–Temporal Tensor Graph Convolutional Network for Traffic Speed Prediction. IEEE Transactions on Intelligent Transportation Systems. 2023; 24(1): 92-104.

[30] Aristotelis-Angelos Papadopoulos, Ioannis Kordonis, Maged Dessouky and Petros Ioannou. Personalized Freight Route Recommendations With System Optimality Considerations: A Utility Learning Approach. IEEE Transactions on Intelligent Transportation Systems. 2023; 24(1):400-411.

[31] Jiexia Ye, Juanjuan Zhao, Kejiang Ye, Chengzhong Xu. `How to build a graph-based Deep Learning Architecture in Traffic Domain : A Survey. IEEE Transactions on Intelligent Transportation Systems. 2022; 23(5) 3904-3924