Estimation of Travel Times for Minor Roads in Urban Areas Using Sparse Data

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***Abstract*—Travel time is a basic measure upon which e.g. traveller information systems, traffic management systems, public transportation planning and other intelligent transport systems are developed. Collecting travel time information in a large and dynamic road network is essential to managing the transportation systems strategically and efficiently. This is a challenging and expensive task that requires costly travel time measurements. Estimation techniques are employed to utilise data collected for the major roads and traffic network structure to approximate travel times for minor links. Although many methodologies have been proposed, they have not yet adequately solved many challenges associated with travel time, in particular, travel time estimation for all links in a large and dynamic urban traffic network. Typically focus is placed on major roads such as motorways and main city arteries but there is an increasing need to know accurate travel times for minor urban roads. Such information is crucial for tackling air quality problems, accommodate a growing number of cars and provide accurate information for routing, e.g. self-driving cars. This study aims to address the aforementioned challenges by introducing a methodology able to estimate travel times in near-real-time by using historical sparse travel time data. The effectiveness of the proposed method is evaluated on a part of Leicestershire traffic network in UK.**

***Index Terms*—travel times, sparse data, estimation, artificial neural network, traffic model**

I. Introduction

TRAFFIC congestion is becoming increasingly problematic issue for major cities across the globe. Accoring to [1] in the United Kingdom the estimated cost of congestion in 2017 was more than £37.7 billion; with London ranked the 7th most congested city in the world. Congestion can be defined as the traffic demand exceeding the roadway capacity. While a number of works were undertaken to increase UK transport network capacity, in urban areas, transportation infrastructure development is constrained by land and financial resources [2]. Another approach to deal with congestion is by improving the current traffic management strategies [3]. However, to effectively respond to daily traffic challenges operators need current travel times data or accurate models of travel time.

Travel time, average speed (the total distance travelled by a vehicle divided by the elapsed time to cover that distance), congestion level (slower speeds, longer trip times, and increased vehicular queueing, etc.), traffic flow (flow of vehicles on a lane) and traffic delay (time difference between actual travel time and free-flow travel time) of a traffic segment/link are intercorrelated. A vital performance indicator of the traffic network is the travel time parameter. Travel time estimation is defined as the method which approximates the travel time of vehicles on a given link during a given period. Data from GNSS equipment, loop detectors, camera surveillance systems and other existing technologies can be used to approximate travel times in near real-time.

Travel time can be measured and collected typically by using stationary observers or moving observers. Stationary observers include loop detectors and video surveillance, which provide flow and speed estimation at regular and frequent intervals. Moving observers, consisting of floating cars, probe cars, vehicle fleets with GPS devices or smartphones, provide information which can be used to extract travel time data in road segments where the moving observers go through [4]. Travel time data source directly influences the property of travel time data. Stationary observers can collect travel time data at regular and frequent intervals. However, the share of segments in the network equipped with these observers is typically low and not representative of the urban network as a whole, which leaves the traffic conditions in most of the network unknown [5]. In contrast, the moving observers can collect travel time data at irregular, less frequent intervals and in limited duration of time, which means that, for a particular time of a day of a road segment, there might not be any travel time data available. Also, the moving observers enable collection of travel time information across the entire urban road network [4], [6].

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The reminder of this paper is organized as follows. Section II reviews the related work. The details of the proposed algorithm are given in Section III, followed by Section IV that evaluates the performance of NLIM-SMS, and conclusions are provided in Section V.

II. Related Work

The existing travel time estimation methods are regularly classified as direct or indirect methodologies [7]. In the direct approach, the travel time is estimated based on data samples obtained from moving observers, e.g. in-car sensor equipment [8]–[10], GNSS-based floating car [6], [11]–[18], automated vehicle identification (AVI) system [4], [14], telecommunication activities [19]–[22]. Furthermore, travel times can be

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estimated from locations of drivers' smartphones, from car satellite navigations systems or large car fleets operators.

The advantage of the direct method is that it requires limited expenses of infrastructure and it is capable of producing travel time data in small roads where loop detectors may not be deployed. The drawback of the direct method is that for example a car cannot collect data in different locations simultaneously. Also at different times the particular road may exhibit different dynamics which may not be captured by a car. Hence, uncovering a methodology for travel time estimation from incomplete datasets receives a great interest from researchers in the field of the intelligent transport systems.

A methodology to estimate the travel time from GNSS vehicle location reports was introduced by [18]. The GNSS signal from vehicles is mapped to real traffic links. Based on the time stamps of the GNSS vehicle location reports, travel time for full traffic link is approximately reconstructed. The interval of travel time is given in 15 minute intervals. The methodology is widely used in the UK for transport management and control, [18], [23].

On other hands, the indirect method uses data obtained by stationary observers, i.e. inductive loop detectors [24]–[27] to analyse the correlation between travel time and traffic flow. The inductive loop detectors are regularly deployed at junctions and segments of major roads. The indirect method can provide travel time data at a regular sampling rate.

For many years an interest in travel time estimation was growing due to its crucial role in intelligent transport systems. Nowadays, for the ongoing Industry 4.0 Revolution, which is expected to impact all disciplines, industries, and economies, the information about travel times of goods and people is even more critical, [7]. As a result different multivariate and univariate methodologies to model travel time are being proposed. Most of the proposed methods use statistical and mathematical techniques. The remaining often utilises artificial neural networks, support vector machines, linear regression, Bayesian methodologies, Monte Carlo Algorithms, queueing and non-linear least square.

A number of earlier research employ statistical methodologies to estimate current travel time data. They include distributions of everyday historical travel time data in a traffic link/segment, [5], [20], [28]–[30], distributions of historical travel time on a complete route [14], [21], travel time histogram [17], [31], [32] and average travel time in link [10], [33], [34].

Mathematical methods for travel time model have recently received interests of researchers. They include a travel time allocation method [35], tensor-based method [36], maximum likelihood [37], indexing trajectories [38], local alignment [22]. Mathematical and statistical methodologies usually perform less accurate in urban traffic network where the traffic condition can be complex.

A number of research on travel time estimation focuses on machine learning techniques such as neural network [7], support vector machine [39], non-linear least square [40], linear regression [39]. And lately, Monte Carlo algorithm [12], [41] and queuing methodology [25] are not considered on recent research.

Machine learning methodologies are regularly data-driven methods. They can learn relationships and create models using unstructured dataset. The approaches are often useful in many transportation applications because they are free of model assumptions and the uncertainty of traffic can be involved in the traffic model.

Recent developments in technology in the Industrial 4.0 Revolution and the non-stop introduction of new technology and powerful computers, big data analytic techniques and mathematical models provide researchers with a phenomenal opportunity to expand the knowledge in travel time estimation domain.

The application of machine learning techniques in traffic models and the development of new data acquisition instrumentation allow researchers to capture or model more precisely dynamics of a large traffic network. In this thesis, machine learning techniques are utilised to develop travel time models for a large size traffic network.

III. Similar Model Searching Method

A. *Definitions*

B. *SMS*

The backbone of this methodology is

IV. Experimental Results

A. *Experimental Data*

Teletrac (formerly Trafficmaster) is a US software company with offices in the United Kingdom. They provide a cloud-based GNSS tracking software for fleet tracking. More than 250,000 vehicles in more than 87 countries have provided tracking information using their software [42].

According to [**?**], a floating car was a concept used to obtain traffic flow and journey time. Since the 2000s, a Floating car is any car from which GPS positions are continually recorded via in-car equipment, smartphones, etc., [6], [11], [14], [15], [20], [30], [39], [43]–[45]. Floating Car Data (FCD) used in this research refers to travel time data which is gathered from GNSS tracking of floating cars by TrafficMaster.

B. *Traffic network*

The travel time data was collected from September 2009 to February 2012 in Leicestershire, UK. The dataset used comprises travel times for 22053 traffic links including 67 motorway links, 22 trunk links, 911 primary link, 1457 A links, 843 B link and 13752 minor links (Table I). In 13752 minor links, 5226 links have data sparsity less than or equal to 99%. They account for 38% of the total minor links. The traffic network is shown in Figure **??**. The raw data collected from FCD contain reconstructed link travel times at 15 minutes intervals. Thereby, a day starting from 00h00 to 23h59, was divided equally into 96 slots. The travel time data unit is 10^{-2} second. The average travel time in minutes per miles for links in the traffic network is approximately 2.46 (minutes/miles). Total links' length is roughly 14,000 kilometres or 8,700 miles. There are nine vehicle classes which are based on the payload and the size of the vehicle. The vehicle classes are shown in

TABLE I
THE NUMBER OF LINKS IN THE DATASET

Link type	Number of links
Motorway	67
Trunk	22
Primary	911
A	1457
B	843
Minor (data sparsity $\leq$ 99%)	5226
Minor (data sparsity $>$ 99%)	8526
	Total: 22053

TABLE II
VEHICLES CLASS

Class (veh_cls)	Description
1	Cars
2	LGVs (up to 3500kg)
3	HGVs (up to 3500kg)
4	HGVs (over 7500kg)
5	Buses (including minibuses)
6	Taxis
7	Motorised caravans
8	Other vehicles
9	Unknown

TABLE III
THE CSV FILE FORMAT USED IN THE FCD DATASET

Data field	Type	Example	Description
TOID	string	4000000019182789A	ITN identifier and direction of the link
Wayness	integer	1	indicate one-way (1) or two-way link (2)
Name	string	ATTERTON LANE	name of the road that contains the link
Number	string	A444	number of the road that contains the link
DescriptiveGroup	string	Named Road	description of the link categories
DescriptiveTerm	string	Minor Road	link category
ChangeDate	date	2007-09-21	date of the map which the link is added
VersionDate	date	2007-09-21	the version date of the map
VersionNumber	integer	432863	version number of the map
StartX	integer	432863	x coordinate of the beginning of the link
StartY	inteer	297610	y coordinate of the beginning of the link
MidX	integer	433971	x coordinate of the middle of the link
MidY	integer	298258	y coordinate of the middle of the link
EndX	integer	435305	x coordinate of the ending of the link
EndY	integer	298329	y coordinate of the ending of the link
LinkLength	integer	2753	the length of the link in Yards

Table II. The travel time data mainly is from TrafficMaster (95%), and a small proportion is from Norwich Union (5%). There are no different format between two travel time data sources. The dataset is in a CSV file format. A CSV file consists of data for an individual link on a monthly basis. The size of total CSV files for Leicestershire traffic network is approximately 60Gb. Table III shows the CSV format of traffic map in the FCD dataset. The LinkLength ranges from 1 to 3860 yards. The average length of links is 117.8703 yards.

The raw data collected from FCD contain reconstructed link travel times at 15 minute intervals. Thereby, a day starting from 00h00 to 23h59, was divided equally into 96-time slots. For example, time slot 34 covers the period from 08:30:00 08:44:59. The travel time data unit is a 10^{-2}second. The average travel time in minutes per miles for links in the traffic network is approximately 2.46 (minutes/miles). Total links' length is roughly 14,000 kilometres or 8,700 miles. There are nine vehicle classes which are based on the payload and the size of the vehicle.

Initially, some frequency histogram of travel times against there values are analysed and data sparsity of travel time in links are calculated in order to give an insight into the complexity, irregularity and sparsity of the dataset. Figure **??** shows the frequency histogram of travel times of several traffic links, Figure 1 graphically illustrates the data sparsity in link over the traffic network and Figure 2 plots data sparsity in links.

Figure **??** graphically shows that the histogram of traffic links is different and the range of travel times in traffic links varies. The travel times range from less than three seconds to over 600 seconds. The figure also graphically describes the distribution of travel times on traffic links have long right tails and different scales. It means that there are some very high travel time values on all studied traffic links. Hence, the preprocessing data for the travel times in the dataset is most likely required. It includes outliers detection/removal and data normalisation.

According to the travel time data that is acquired from Leicestershire from 2009 to 2012, the data sparsity of links visually shows very high values in Figure 1 where data sparsity is presented by colour on map for every links. Figure 2 indicates that 69.42% of total links have data sparsity is less than or equal to 99%. Figure 2 shows that the number of travel time samples is different by the time of the day. There are more travel time data for the time interval between 7am and 7pm. NLIM is proposed for large scale traffic networks, hence it should perform well for most of the links in the traffic networks.

The FCD dataset which is a real historical travel time dataset is used to assess the performances of NLIM. The NLIM employed MLR, FF-EL-ANN and FF-RPROP-ANN are trained on the dataset. The performance metrics of NLIM models are given by using unseen data. After that, the performances of NLIM models will be compared to the achievements of NLIM models on three previous datasets. As discussed in the previous section, due to the long training time on a large number of labelled data and less accurate of SVR-LK models, so it is eliminated in this experiment.

To demonstrate the advantages of NLIM models in different machine learning techniques, their performance is compared with those of Historical Average (HA) and Moving Average (MA) methods [36]. HA and MA are typical standard methods that allow estimating the current travel time by using historical travel time data. HA uses the corresponding average of the historical travel time of a time slot on a target link to estimate the current time slot travel time on the link. Meanwhile, MA uses moving average of three-time slots right before the current time slot to estimate the current time slot travel time [36].

Input features for training and testing NLIM models in a link layout using the proposed method are sparse historical travel time of neighbouring links, time of day(time slot), vehicle class and day of a week. Day of a week is inferred from the date. Output feature is travel time corresponding to the input features of a target link.

13527 links produce 13527 link layouts. There are 338177 traffic link models in total. The models are carefully trained and verified to make sure relationships between temporal

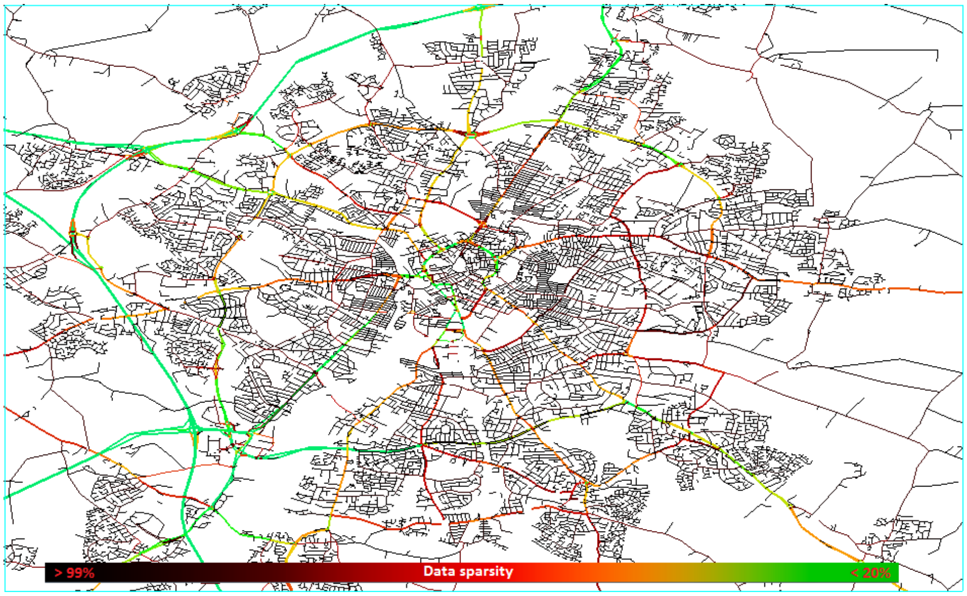

Fig. 1. Illustrating the data sparsity in the dataset for the traffic network in Leicestershire, UK.

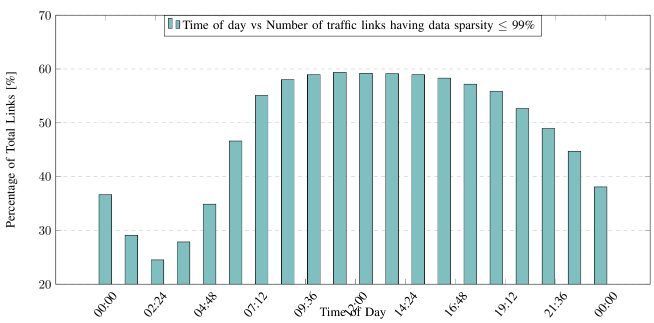

Fig. 2. Illustration the data sparsity in links by the time of day.

and spatial of travel times in links correctly learnt. The performances of models are evaluated by RMSE, MAE and MAPE performance metrics on unseen data. Outliers of data set on 13527 traffic links are detected and removed using the proposed DR-M-GMM (Algorithm **??**). The parameter k and γ are set up as mentioned in Section **??** (k = 5, γ = 0.1).

C. Results

V. Conclusions

Improving the performance of NLIM in minor links which have datasets with high data sparsity and irregularity links has been considered in this section. The main idea is to adapt travel time data of similar NLIM models to improve a selected NLIM model. The similar model searching (SMS) has been evaluated on FCD dataset. NLIM was firstly used for traffic links to create a collection of NLIM models. Then, the similar model searching method was applied. Results show that SMS is capable of improving the performance of NLIM on learning the temporal and spatial relationship between the travel time of a target link and travel time of its neighbouring link despite the high data sparsity and irregularity of the dataset.

Appendix
Algorithms

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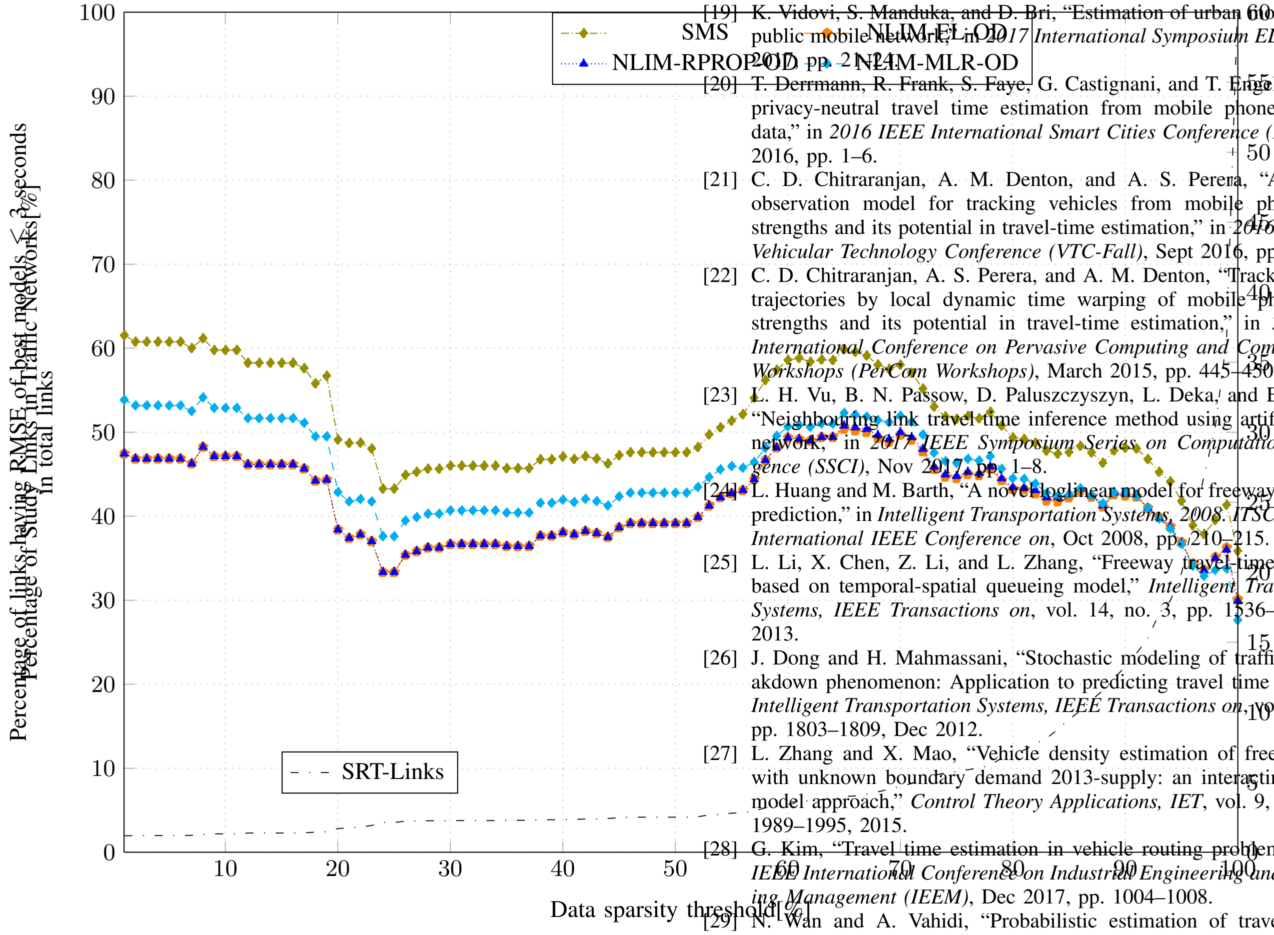

Fig. 3. Percentage of links that have RMSE of the best model less than or equal to 3 seconds vs sparsity threshold achieved by Neighbouring link inference method with similar model searching (SMS), NLIM employed FF-EL-ANN (NLIM-EL-OD), NLIM employed FF-RPROP-ANN (NLIM-RPRO-OD), NLIM employed MLR (NLIM-MLR-OD) on the unseen data. Outliers are identified and removed from the unseen test data by applying Algorithm **??**.

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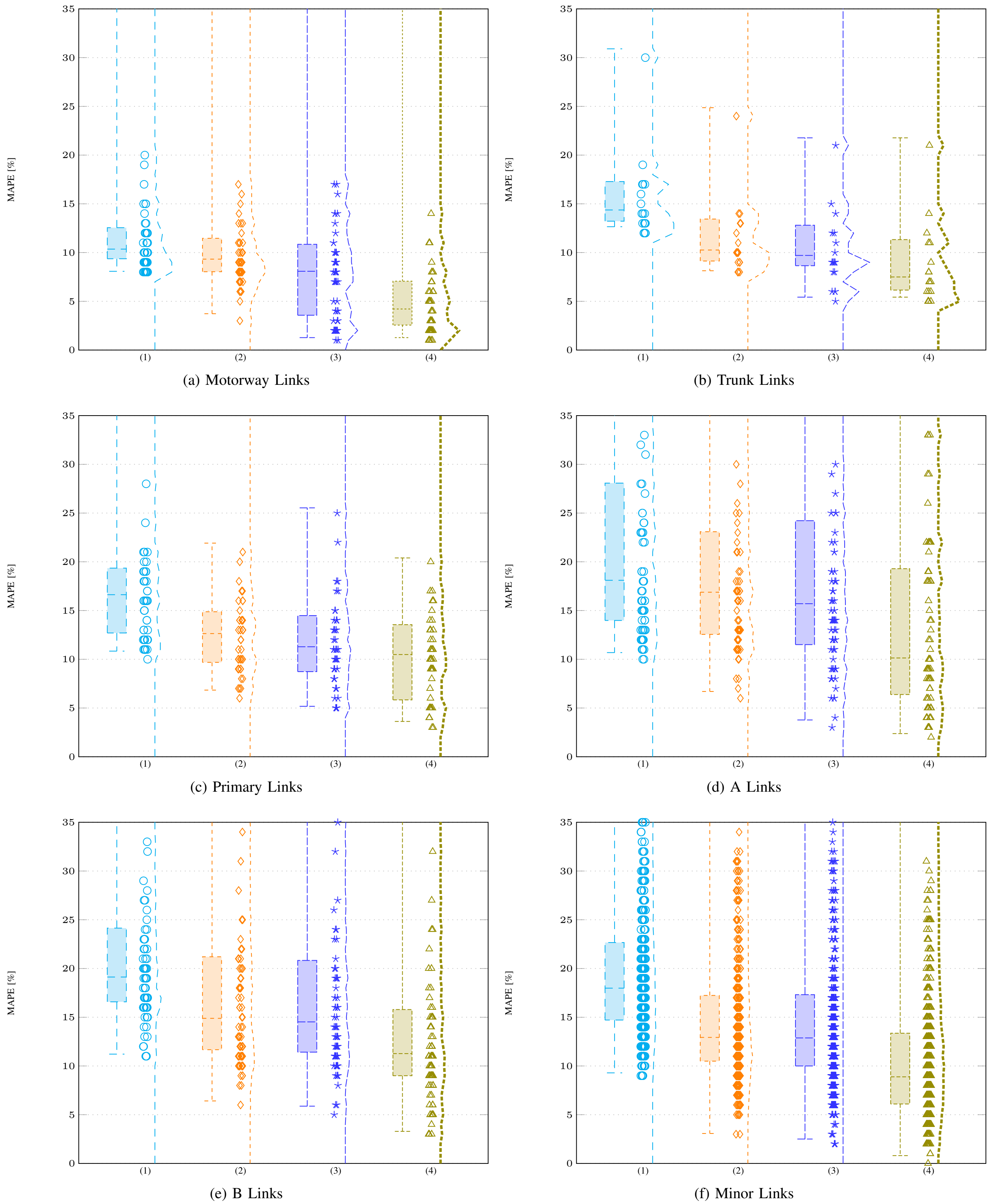

Fig. 4. Density of the best NLIM models, different machine learning techniques applied, of Motorway (a), Trunk (b), Primary (c), A (d), B (e) and Minor (f) links and their MAPEs [%] achieved on unseen data. Sub-figures are in the same scale. (1) is for MLR, (2) is for FF-EL-ANN, (3) is for FF-RPROP-ANN and (4) is for SMS. The density of best models in each method is presented by boxplot (lower whisker, lower quartile, median, upper quartile, upper whisker), visualisation of the actual individual model and the histogram of the models respectively. Some high MAPE data points are out of the figure, hence corresponding upper-whiskers can not be shown.

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