3D Speed Maps for Short-Term Urban Traffic Prediction

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ABSTRACT

City-wide travel time prediction in real-time is an important enabler for efficient use of the road network. It can be used in traveler information to enable more efficient routing of individual vehicles as well as decision support for traffic management applications such as directed information campaigns or incident management. 3D speed maps has been shown to be a promising methodology for revealing day-to-day regularities of city-level travel times and possibly also for short-term prediction. In this paper we aim to further evaluate and benchmark the use of 3D speed maps for short-term travel time prediction, and to enable scenario-based evaluation of traffic management actions we also evaluate the framework for traffic flow prediction. The 3D speed map methodology is adapted to short-term prediction and benchmarked against historical mean as well as against Probabilistic Principal Component Analysis (PPCA). The benchmarking and analysis is made using one year of travel time and traffic flow data for the city of Stockholm, Sweden. The result of the case study shows very promising results of the 3D speed map methodology for short term prediction of both travel times and traffic flows. The modified version of the 3D speed map prediction outperforms the historical mean prediction as well as the PPCA method. Further work includes extended evaluation of the method for different conditions in terms of underlying sensor infrastructure, preprocessing and spatio-temporal aggregation as well as benchmarking against other prediction methods.

Keywords: short-term, travel time prediction, traffic prediction, demand prediction, spatio-temporal clustering, 3D speed map
INTRODUCTION

City-level short-term travel time prediction is important for both traveler information and traffic management applications. Travel time prediction for traveler information enables better utilization of the existing road network through improved distributed route choice of individual travelers. In proactive traffic management travel time prediction enables better use of the road network through centralized decisions on directed traveler information, traffic control or incident management strategies.

3D speed maps, where traffic data are clustered jointly in space and time based on the structure of the underlying road network, has been shown to be a promising methodology for revealing day-to-day patterns in road network performance [9]. Further, the potential for using the 3D speed maps for computationally efficient short-term prediction of travel times for city level networks is also indicated [9]. In this paper we aim to further evaluate and benchmark the use of 3D speed maps for short-term travel time prediction.

Travel times have in the past years become relatively easy to observe with large spatio-temporal network coverage using probe data. Travel time is a good indicator of the road network performance, but is a result of both traffic demand and supply. When the supply is changed, e.g. due to incidents, the same demand can result in very different performance. An important part of proactive traffic management is scenario evaluation, i.e. evaluating possible management actions based on the predicted demand and choosing the action with the best predicted result. This requires good supply modeling as well as modeling of the management actions, but also a reasonably accurate prediction of the demand. For actions that affect large parts of the city road network, it is important to predict demand at the city level. Currently, this evaluation is mainly performed ex post and can be affected by various circumstances, e.g. the specific incident impact, current traffic demand, travel times and information provided to users. In this context, we extend predictions of the road network performance (travel times) to include traffic demand (traffic flow observations) in order to enable large-scale demand prediction for real-time scenario evaluation of traffic management actions.

Most research on short-term travel time prediction has focused on motorways and major arterials (1,2). Naive methods such as the historical mean or instantaneous travel time without model assumptions are easily implemented, computationally effective and, therefore, widely used in practice (3). Commonly applied models also include artificial neural networks (3,4). Another approach utilizes Dynamic Traffic Assignment (DTA) models (5,6). However, while these models are behaviorally rich and can capture driver response to traffic information, they are complex and their calibration and application is challenging. Sophisticated models commonly applied in smaller case studies of motorways are computationally complex due to the number of inputs and parameters that have to be continuously calibrated. Probe data-driven travel time prediction for expressways based on matching similar spatiotemporal traffic patterns is introduced in (7).

Urban network travel time prediction is a more complex and challenging problem compared to motorways due to the many uncertainties involved, which are difficult to measure or predict. The uncertainties in the urban environment are: signalized and unsignalized intersections; many routing alternatives; crossing with pedestrians and other traffic flows; etc. Furthermore, network-wide prediction is often associated with noisy and missing data. With the increasing availability of probe data, the literature on arterial travel time estimation and prediction has grown recently (7–13). Network-wide travel
time prediction combining advantages of Probabilistic Principal Component Analysis (PPCA) and local smoothing is proposed in (10) and extended into an integrated framework for real-time urban network travel time prediction on sparse probe data in (8). This framework is versatile and can be used with any source of travel time data, as well as for a large-scale mixed networks. A recent study (14) uses consensual 3D speed maps (where the three dimensions are $x$ and $y$ location coordinates plus time as the third dimension) representing the day-to-day regularity on the networks to predict travel times.

An important part of many data-driven methods for traffic prediction is preprocessing of the data in terms of clustering. There is an extensive amount of literature in the context of partitioning/clustering methods. It is widely used in different fields such as location analysis, zoning/distancing, aggregation, data science, mathematics, transport research, GIS, etc. K-means (15) is one of the most popular clustering techniques. Another commonly used clustering algorithm is a density-based algorithm for discovering clusters in large spatial databases with noise (DBSCAN) (16). Recent developments in clustering for transportation networks extend normalized cut (NCut) (17) with snake similarities (S-NCut) (18). K-means, DBSCAN and S-NCut are compared in (9) on a city road network and travel time data, and it is shown that k-means can be a very good trade-off between the quality of resulting clustering and computational time.

There is still limited research considering spatio-temporal partitioning of large-scale networks in the context of travel time prediction. In most of the literature, one route or several routes are usually considered independently. To the best of our knowledge, only the recent study (9) considers spatio-temporal partitioning and day classification for large-scale networks. The study discusses the applicability of the 3D speed maps (14) in revealing day-to-day regularities towards day classification. It is proposed for each group of days to establish the consensual 3D speed map shape, which represents a particular group, by consensual clustering. Because of the complexity of the consensual clustering, the one random move heuristic (19) is used. The methodology proposed in (9) enables virtual visualisation of different types of days on the whole network, and thus it is very promising for use in traffic management, urban planning and policy. The main contribution of (9) is the revelation of day-to-day regularity of congestion patterns with consensual 3D speed maps, which can be easily visualised and studied. In addition, a simple and real-time travel time prediction methodology that matches the current day with one of the consensual 3D speed map shapes in order to predict for a future time interval is introduced. The whole concept is very promising for city-level short-term prediction. Thus, inspired by (9), we compare the proposed methodology of short-term travel time prediction with other prediction methods such as PPCA (8,10), historical mean and our modification of the 3D speed map prediction methodology.

The main contribution of this work is the modification of the 3D speed maps prediction methodology presented in [9] for short-term travel time prediction, as well as a computational study and comparison with different prediction methods. The modifications can be summarized into three points. First, the calibration of the number of considered past intervals while predicting for just one future time interval. The number of considered past intervals affect the revealing of day-to-day regularities with the day classification and identification with revealed historical patterns (consensual 3D speed map shape of the groups in (9)). To calibrate how deep the method looks back in time has the potential to remove undesired closeness to the historically revealed patterns and to enable better matching for the short-term prediction. This can result in better pattern recognition, as well as more accurate short-term travel time prediction. Second, each source of data is considered individually in matching with the revealed historical pattern as in the prediction. The original methodology is not considering the sources
independently. The 3D speed maps consist of the spatio-temporal clusters and the mean values within this
clusters are considered in matching the current day with the closest consensual 3D speed map shape. This
aggregation involves the potential aggregation errors that will grow with the size of aggregation, although
it can eventually help on small case studies with noisy data. Third, we investigate the use of the median
centroid vectors instead of consensual 3D speed map shapes. Median centroid vectors provide a simpler
and computationally effective way of creating centroids for the group of days, where a vector provides for
each source and time interval the median value across the grouped days.

The computational experiments reveal improvements in the prediction accuracy and robustness of
the proposed methodology. The proposed methodology is compared with the original consensual 3D
speed maps methodology proposed in (9) and with the PPCA prediction method (8,10) on two different
case studies in Stockholm, Sweden. First, the 15 point sources of the speed from the loop detectors are
considered. Second, the 420 sources of the travel time/speed and traffic flow processed from the loop
detectors into the defined routes are studied.

The paper is organized as follows. The methodology section presents the new methodology and
highlights the differences with the original consensual 3D speed maps methodology. Data, case studies
and design of the computational experiments are introduced in the next section: Data and Case Study. In
the result section, the results of the computational experiments are presented. Finally, the last section
contains our concluding remarks.

METHODOLOGY

In this section, the modified methodology of (9) for short-term prediction, that uses the 3D speed maps
and consensual clustering to represent different types of days, is presented. The methodology can be split
into three parts: (i) classification of days; (ii) calibration; and (iii) real-time travel time prediction with
group identification. The proposed adjustments to the methodology of (9) are highlighted in more detail in
the relevant subsections, below.

The methodology is versatile and applicable for different sources of speed/travel time and traffic
flow data. There is a broad range of different technologies, e.g., GPS, loop detectors, and Bluetooth
sensors that enable estimation of travel times and traffic flows. These speed and flow data can be
processed to points, links or routes sources of data. The travel times are not usually determined just for a
one point. In the methodology section, we refer to any sensor, detector, point, link or route with
speed/flow/travel time information as a source. The notation is summarized in Table 1 and Figure 1 shows
the framework of the modified methodology.
<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k, l$</td>
<td>index for day</td>
</tr>
<tr>
<td>$K$</td>
<td>number of the days</td>
</tr>
<tr>
<td>$i$</td>
<td>index for source</td>
</tr>
<tr>
<td>$I$</td>
<td>number of sources</td>
</tr>
<tr>
<td>$j$</td>
<td>index for time interval</td>
</tr>
<tr>
<td>$J$</td>
<td>number of the time intervals</td>
</tr>
<tr>
<td>$c_{ijk}$</td>
<td>spatio-temporal cluster ID of the source $i$ on time interval $j$ and day $k$</td>
</tr>
<tr>
<td>$v_{ijk}$</td>
<td>speed/flow/travel time on the source $i$ in time interval $j$ and day $k$</td>
</tr>
<tr>
<td>$\gamma_k$</td>
<td>3D speed map or vector representing the day $k$ by cluster IDs labels $c_{ijk}$</td>
</tr>
<tr>
<td>$\delta_k$</td>
<td>3D speed map or vector representing the day $k$ by speed/flow values $v_{ijk}$</td>
</tr>
<tr>
<td>$\lambda_p$</td>
<td>centroid vector of the group $p$ considering each source and time interval</td>
</tr>
<tr>
<td>$\nu_{ij}$</td>
<td>median or mean speed/flow/travel time of the source $i$ in time interval $j$ across days that are in the group $p$</td>
</tr>
<tr>
<td>$\tau_p$</td>
<td>consensual shape vector</td>
</tr>
<tr>
<td>$r$</td>
<td>index/label of the consensual shape vector cluster</td>
</tr>
<tr>
<td>$\nu_{rp}$</td>
<td>the mean speed/flow across all sources and time intervals and days of the consensual shape cluster $r$ of the group $p$</td>
</tr>
<tr>
<td>$\lambda_{rp}$</td>
<td>the mean speed/flow across all sources and time intervals at day $k$ when applying the consensual shape cluster $r$ of the group $p$</td>
</tr>
<tr>
<td>$p$</td>
<td>index for group</td>
</tr>
<tr>
<td>$P$</td>
<td>number of the groups</td>
</tr>
<tr>
<td>$G_p$</td>
<td>set of days in the group $p$</td>
</tr>
<tr>
<td>$G$</td>
<td>set of the $P$ groups</td>
</tr>
<tr>
<td>$N_C$</td>
<td>calibration set of days</td>
</tr>
<tr>
<td>$N_E$</td>
<td>evaluation set of days</td>
</tr>
<tr>
<td>$N_T$</td>
<td>training set of historical days used for revealing the 3D speed maps centroids</td>
</tr>
</tbody>
</table>
Revealing day-to-day regularities with 3D speed maps

Initialization of parameters

Initialization of input data

DB with traffic data

$N_T$

$N_C$

1 $v_{t,1}, \ldots, v_{t,J}$

K $v_{t,K}, \ldots, v_{t,J}$

n $v_{f,1}, \ldots, v_{f,J}$

create 3D speed map

$\delta_{i,j}$

$\delta_{K}$

$\delta_{K,j}$

create similarity matrix

<table>
<thead>
<tr>
<th>1</th>
<th>K</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>K</td>
<td>$CS(K,1)$</td>
</tr>
</tbody>
</table>

days classification

$G_1, \ldots, G_p$

select centroid vector

$\lambda_1, \ldots, \lambda_p$

group identification and prediction

$P < P_{\text{max}}$

also

$I < I_{\text{max}}$

also

$F < F_{\text{max}}$

true

false

false

false

true

P = 1, t = 1, f = 1 + 1

P = 1, t = t + 1

P = 1, t = t + 1

P = 1, t = 1, f = f + 1

centroid vectors with best prediction performance

FIGURE 1 Framework of the modified methodology of using 3D speed map for short-term travel time prediction with calibration. (a) Process flow of revealing the day-to-day regularities. (b) Illustration of integrating the pre-computed centroid vectors for real-time prediction.
Classification of days

The methodology in (9) reveals day-to-day regularity. The 3D speed map of day $k$ is the result of k-means clustering (15) and it is represented by the single ordered vector of all $I$ sources of travel time and $J$ time intervals observations $\gamma_k = \left( c_{ijk}, \ldots, c_{ijk} \right)$, where $c_{ijk}$ is the k-means cluster ID label of source $i$ in time interval $j$ on day $k$.

In order to evaluate if the 3D speed map representation $\gamma_k$ in (9) is appropriate for short-term prediction purposes, we propose to represent a day $k$ by the 3D speed map in the form of the single ordered vector of speed/flow values $\delta_k = \left( v_{ijk}, \ldots, v_{ijk} \right)$. To measure the similarity between two days, the normalized mutual information (NMI) used in (9) is not appropriate for this case, because it measures the similarity of two days $k$ and $l$ by mutual information of the cluster’s labels in two 3D speed map vectors $\gamma_k$ and $\gamma_l$. Thus, the similarity between two days $k$ and $l$, where $k \neq l$, is here measured by the cosine similarity $CS(k, l)$ as:

$$CS(k, l) = \frac{\sum_{i=1}^{I} \sum_{j=1}^{J} \delta_{ik} \delta_{ij}}{\sqrt{\sum_{i=1}^{I} \sum_{j=1}^{J} \delta_{ik}^2 \sum_{i=1}^{I} \sum_{j=1}^{J} \delta_{ij}^2}}$$

The classification of the $K$ days into $P$ groups, is the same for both methods and it is performed using the Ncut algorithm (20) with the similarity matrix of $K \times K$ values $CS(k, l)$, for $k, l = 1, \ldots, K$. The centroid of group $p$ represents all days of group $G_p$. In (9), consensual clustering is used to produce a consensual 3D speed map shape or vector $\tau_p = \left( c_{ijk}, \ldots, c_{ijk} \right)$ representing the groups. Because of computational complexity they adopt a simple one random move heuristic presented in (19). The consensual 3D speed map shape $\tau_p$ of the group $p$ is used in the form of the cluster means $\nu_{r_p}$ to match the group or predict for a future time interval. Because of this aggregation that can involve aggregation errors that can grow with the size of the case study, we investigate a different approach that considers each source $i$ and time interval $j$ independently. We propose to select for a each group $p$ a centroid vector $\lambda_p = \left( v_{ij}^p, \ldots, v_{ij}^p \right)$, where $v_{ij}^p = \text{median} \left( v_{ijk} \right)_{k \in G_p}$ or $v_{ij}^p = \text{mean} \left( v_{ijk} \right)_{k \in G_p}$ represents the median/mean value for source $i$ and time interval $j$ across days belonging to group $p$. This approach is significantly less time consuming than the consensual clustering and does not involve aggregation of the links and time intervals.

Calibration

The prediction methodology proposed in (9) does not include any automatic calibration. Calibration can be performed in different ways. We propose to calibrate the day classification based on day-to-day patterns for each time interval individually, instead of considering long day-time periods (e.g. the whole day or the peak period). This can be achieved by calibrating a number of past $t$ or future $f$ time intervals; if $c$ represent the current time interval and the aim is to predict travel time for the future interval $c + 1$ then
the combination of \( t \) past intervals and \( f \) future intervals is iterated in the calibration process. The settings of the parameters with the best prediction performance on a calibration set of days \( N_C \) is used to store the groups of days within its centroid vectors.

**Real-time travel time prediction with group identification**

First, the original methodology (9) for matching the current day with consensual 3D speed map vectors and short-term prediction is introduced. (9) defines \( y_{rp} \) to represent the mean speed/flow value across all sources, time intervals and days with the cluster \( r \) of the consensual 3D speed map centroid \( \tau_p \). The mean speed/flow of cluster \( r \) for the day \( k \) is denoted as \( x_{rp}^k \) if the same cluster of the consensual shape vector \( \tau_p \) of the group \( p \) is applied. Only clusters containing some of the past time intervals until the current time interval \( c \) are used to find the group index \( p^* \) that minimizes the Euclidean distance between the current day \( k \) and group can be found as:

\[
p^* = \arg \min_{p \in G} \left( \frac{1}{n} \sum_{r=1}^{n} (x_{rp}^k - y_{rp})^2 \right)
\]

Then prediction for each source \( i \) in the future time interval \( c+1 \) is extracted as the mean of \( y_{rp} \) cluster that contain particular source \( i \) at future time interval \( c+1 \). The sources and time intervals are not considered individually, but network-wide minimisation of the euclidean distance is prefered. This aggregation can introduce errors when predicting the travel time, especially for larger case studies. Therefore we propose the opposite extreme, where each time interval and source are considered individually.

When predicting the travel time for source \( i \) at day \( k \) and current time interval \( c \), one of the \( P \) groups with the centroid vectors \( \lambda_p \) needs to be selected as the potentially best predictor for time interval \( c+1 \). The \( p^* \) that minimizes the Euclidean speed/flow distance across \( t \) past intervals of the current day \( k \) vector \( \delta_k = (v_{ic-t,k}, \ldots, v_{ic}) \) to one of the groups’ centroid vectors \( \lambda_p = (v_{ic-t}^p, \ldots, v_{ic}^p), \ p = 1, \ldots, P \) is selected:

\[
p^* = \arg \min_{p \in G} \left( \frac{1}{t} \sum_{j=c-t}^{c} (v_{ijk} - v_{ijk}^p)^2 \right)
\]

Knowing the group and centroid vector \( \lambda_{p^*} \) for the source \( i \), the speed/flow of the source \( i \) for the future interval \( c+1 \) can be predicted in a very effective way as the speed/flow value of the centroid \( v_{ic+1}^p \).

**DATA AND CASE STUDY**

In this study we consider two different metrics for prediction, link travel time estimations and flow observations. Both metrics are based on radar measurements from the motorway control system (MCS) around the inner city of Stockholm, Sweden. Two case studies of different sizes and representing also different sources are considered in order to demonstrate the performance of the methods for different
applications. First, speed data from 15 selected MCS radars are used (see Figure 2 (points)). The selected sensors are located on different main routes in Stockholm. Second, data from approximately 2000 MCS radars are used to estimate link travel times on 420 links on the major roads around Stockholm (see Figure 2 (lines)). The link travel time estimation combines the MCS speed data with a first order traffic model (CTM-v) using an ensemble Kalman filter, see (21) for a more detailed description. Data for the whole year 2016 are aggregated into 15-minute time intervals; only days with no missing data in the afternoon peak period (14:45-19:45), are used for this study.

![FIGURE 2 Visualization of the case studies.](image)

**Computational experiments**

To compare the methodology proposed above with other methods, the afternoon peak period (14:45-19:45) for 180 working days during 2016 is considered. Weekends, school and public holidays are filtered out, as well as days with some missing data. 30 days are used as the calibration set of days $N_C$ and other 30 days as the evaluation set $N_E$. The remaining days $N_T$ (120 days for sensors and 127 days for routes) are used as the historical data to reveal the day-to-day patterns. In the experiments, different settings of the proposed approach are evaluated against the original 3D speed maps classification and prediction (9) (noted as NMI_consensus method in Table 2), PPCA (8,10) and the historical mean.

Performance using mean or median centroids was very similar, with median centroids performing slightly better. We therefore present only the results for the median centroids. The list of investigated methods with notation and description is presented in Table 2.
TABLE 2 Notation of the methods considered for computational experiments

<table>
<thead>
<tr>
<th>Notation</th>
<th>3D speed map</th>
<th>similarity measurement</th>
<th>interval ( t ) (min/max)</th>
<th>the number of time intervals used for calibration</th>
</tr>
</thead>
<tbody>
<tr>
<td>CS_median</td>
<td>( \delta_k )</td>
<td>CS</td>
<td>20/20</td>
<td>20</td>
</tr>
<tr>
<td>CST_median</td>
<td>( \delta_k )</td>
<td>CS</td>
<td>1/5</td>
<td>1</td>
</tr>
<tr>
<td>NMI_median</td>
<td>( \gamma_k )</td>
<td>NMI</td>
<td>20/20</td>
<td>20</td>
</tr>
<tr>
<td>NMI_consensus</td>
<td>( \gamma_k )</td>
<td>NMI</td>
<td>20/20</td>
<td>20</td>
</tr>
<tr>
<td>NMI_t_consensus</td>
<td>( \gamma_k )</td>
<td>NMI</td>
<td>1/5</td>
<td>1</td>
</tr>
<tr>
<td>NMI_t_median</td>
<td>( \gamma_k )</td>
<td>NMI</td>
<td>1/5</td>
<td>1</td>
</tr>
<tr>
<td>Historical mean</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>PPCA</td>
<td>-</td>
<td>-</td>
<td>1/5</td>
<td>1</td>
</tr>
</tbody>
</table>

Methods with prefix “CS” are using the 3D speed map vector \( \delta_k \) with absolute speed values and CS similarity metric. In contrast, methods with prefix “NMI” use the 3D speed map vector \( \gamma_k \) to represent days and NMI similarity metric when constructing the similarity matrix. Methods with the letter \( t \) involve calibrating the prediction towards the single time interval \( c + 1 \), and methods without the letter \( t \) are calibrating parameters for all involved 20 time intervals. The \( \text{NMI} \_\text{consensus} \) method represents the method proposed in (9), and the full modified methodology proposed in this study is applied in the \( \text{CST} \_\text{median} \) method. When comparing the \( \text{NMI} \_\text{consensus} \) and \( \text{NMI} \_\text{median} \) methods, the effect of the centroid vector \( \lambda_p \) and considering the sources and time intervals individually on the prediction is investigated. Considering \( \text{NMI} \_\text{consensus} \) and \( \text{NMI} \_t \_\text{consensus} \) reveals outcomes of the calibration for the one future time interval instead of all 20 time intervals at once, similarly as for \( \text{CS} \_\text{median} \) and \( \text{CST} \_\text{median} \).

For all methods calibrating the number of past intervals \( t \), the maximal number of past intervals is set to 5 (i.e., 75 minutes). Only one future time interval \( f = 1 \) is considered here. All methods are calibrating the number of groups \( P \). The maximal number of group is set to 15 and the maximal number of k-mean clusters for 3D speed maps \( \gamma_k \) is 15 for the sensors case study and 25 for the routes. The one random move algorithm in the consensus clustering stops if 100 consecutive attempts did not improve the consensus cluster within the group. Because the k-means and grouping of the days involved randomness, we run 10 repetitions for each setting, and the one performing the best on the calibration set of days \( N_C \) is considered.
RESULTS

Short-term travel time prediction

Accuracy of travel time prediction is evaluated in terms of the mean absolute error (MAE) between predicted speeds $\nu_{pf}^*$ and observed speeds $\nu_{qf}$ in the future time interval $f$ across the $N_E$ days and $I$ sources:

$$MAE(f) = \frac{1}{IN_E} \sum_{i=1}^{I} \sum_{k=1}^{N_E} |\nu_{qf} - \nu_{pf}^*|$$

Figure 3 shows the prediction accuracy of all considered methods across the afternoon peak time intervals. The overall average statistics across time intervals are summarized in Table 3.

<table>
<thead>
<tr>
<th>case study</th>
<th>CS median</th>
<th>CSt median</th>
<th>NMI median</th>
<th>NMI consensus</th>
<th>NMI consensus</th>
<th>NMIt mean</th>
<th>PPCA</th>
<th>Historical mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>sensors</td>
<td>3.150</td>
<td>2.786</td>
<td>2.979</td>
<td>3.921</td>
<td>3.582</td>
<td>2.744</td>
<td>3.140</td>
<td>4.312</td>
</tr>
<tr>
<td>routes</td>
<td>2.083</td>
<td>1.920</td>
<td>2.257</td>
<td>12.105</td>
<td>11.141</td>
<td>2.113</td>
<td>2.898</td>
<td>3.660</td>
</tr>
</tbody>
</table>

The $NMI_{consensus}$ and $NMIt_{consensus}$ methods perform the worst among all methods, although the calibration of $t$ past intervals helps to improve the prediction performance for $NMIt_{consensus}$. It reveals, that the weakness of the consensus centroid is that it is not considering sources individually, and the predicted value is the mean $\nu_{rp}$ across all sources and time intervals and days aggregated into the same consensus cluster $r$ of the group $p$. This aggregation error can grow rapidly with the size of the case study, as is evident in Figure 3(b). Calibrating the number of past intervals that should be considered when predicting the travel time can improve the travel time prediction accuracy for all presented methods.

Considering only the versions using the centroid vector $\lambda_p$ with median values, the results show that $CSt_{median}$ is performing better than $NMIt_{median}$ with growing size of the case study. Although, for smaller case studies as with the sensors, the 3D speed maps $\gamma_k$ with NMI measurement can be slightly better. For a small number of sources and time intervals, the number of k-means clusters of the 3D speed maps can be calibrated to maximal number if each source and time interval can have own cluster. In this extreme situation, all days will be considered as the same and grouping of days will generate random groups. Thus, it can by chance create groups that generate median values that can cover some future days slightly better.
FIGURE 3 Accuracy of the prediction methods when predicting travel times. Results are evaluated in terms of mean absolute error (MAE). (a) Sensors case study. (b) Routes case study.

Short-term demand/traffic flow prediction

Traffic flows vary a lot among different routes and thus instead of MAE, the accuracy of traffic flow prediction is measured by mean absolute percentage error (MAPE) between predicted flows $v_{fk}$ and observed flows $v_{ik}$:

$$MAPE(f) = \frac{1}{N_f} \sum_{i=1}^{N_f} \sum_{k=1}^{N_E} \left| \frac{v_{ik} - v_{fk}}{v_{ik}} \right|$$

Figure 4 presents the results of the short-term flow prediction for larger route case studies. Similarly to the results for the speed/travel time prediction, the results of the short-term flow prediction show that the methods $NMI_{consensus}$ and $NMI_{lt\_consensus}$, which both involve consensual 3D speed map vector for
matching and prediction, are clearly performing the worst with MAPE errors exceeding 200%. On the other hand, the most accurate method \textit{CSt\_median} exhibits MAPE errors in range from 10\% to 16\%.

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure4}
\caption{Accuracy of the prediction methods when predicting traffic flows for routes case study. Results are evaluated in terms of mean absolute percentage error (MAPE).}
\end{figure}

\textbf{Computational time}

Table 4 summarizes computational time and shows that the consensus clustering is the most time consuming process, even when using the random heuristic. Thus, the methods using the 3D speed map centroids with median speed values $\lambda_p$ can lower the computational time significantly. Methods using the 3D speed map of speed values $\delta_k$ are faster, because there is no need to compute k-means clusters for the 3D speed maps $\gamma_k$. However, as expected, the methods calibrating each time interval independently need more computation time.
TABLE 4 Calibration computational time in minutes for all methods and 20 time intervals.

<table>
<thead>
<tr>
<th>case study</th>
<th>CS_ median</th>
<th>CSt_ median</th>
<th>NMI_ median</th>
<th>NMI_ consensus</th>
<th>NMIt_ consensus</th>
<th>NMIt_ median</th>
<th>PPCA</th>
<th>Historical mean</th>
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<td>14</td>
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<td>461</td>
<td>572</td>
<td>4021</td>
<td>941</td>
<td>2334</td>
<td>-</td>
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</tbody>
</table>

CONCLUSIONS

Short-term travel time and traffic flow prediction for large-scale mixed road networks is an important but challenging problem. A recent study on revealing day-to-day patterns with 3D speed maps (9) has shown to be promising for finding regularities in city-level road network congestion and potentially also in robust short-term travel time prediction. The aim of this paper is to further evaluate and benchmark the use of 3D speed maps for short-term prediction of travel times and extend it to also include prediction of traffic flows. We propose a modified methodology for improving the outcome of the 3D speed maps in short-term prediction. The computational experiments demonstrate the applicability and performance of the original methodology, as well as the modified methodology with the PPCA and historical mean when predicting travel time and traffic flow on two case studies of Stockholm, Sweden. The new modified methodology outperforms the PPCA, historical mean and original methodology (9) for travel time as well as traffic flow short-term prediction.

Outcomes of the computational experiments can be summarized into four main points. Prediction accuracy is improved by calibrating the number of past intervals used for predicting one time interval ahead. The computational time can be significantly reduced by using median centroid vector compared to using consensual 3D speed map. Using 3D speed maps with speed values and cosine similarity as the metric for the similarity matrix is more robust across different sizes of case studies. The modified methodology outperforms the PPCA prediction method. It is important to note, however, that the proposed method is not appropriate for sources of data with a lot of missing observations. It is crucial to know past observations in order to match with the right centroid vector. If the source of data is not sufficient then the PPCA may be a more appropriate prediction method.

City-level prediction of the traffic state as well as the traffic demand is important for both traveler information applications, such as online navigation, and traffic management applications, such as scenario evaluation of incident management strategies. However, city-level prediction is very challenging and requires efficient processing of large amounts of data. 3D speed maps has already been shown to be efficient for finding day-to-day regularities of traffic patterns and promising for robust prediction of road network performance and here we further establish that the method has large potential for short-term travel time prediction compared to basic methods as well as more advanced and previously used methods for travel time prediction. Furthermore, we show that the method can be extended to large scale traffic flow prediction allowing it to be used in more advanced traffic management applications such as real-time scenario evaluation.

The result of the prediction depends on local factors like the underlying supply and demand variation, but also on generic factors such as: type of preprocessing, type and quality of sensing
infrastructure and spatio-temporal aggregation. More work is needed to evaluate the full potential of using 3D speed maps for road network performance and traffic demand prediction, but the results are very promising for traffic management in the context of city-level scenario evaluation.

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Author contribution statement

The authors confirm contribution to the paper as follows: study conception and design: M. Cebecauer, D. Gundlegård, E. Jenelius, W. Burghout; data collection: D. Gundlegård, M. Cebecauer; analysis and interpretation of results: M. Cebecauer; draft manuscript preparation: M. Cebecauer, D. Gundlegård, E. Jenelius, W. Burghout. All authors reviewed the results and approved the final version of the manuscript.

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