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A METHOD TO ESTIMATE TRAFFIC PENETRATION RATES OF COMMERCIAL FLOATING CAR DATA USING SPEED INFORMATION

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Abstract. Floating Car Data (FCD) are being increasingly used as an alternative traffic data source due to its lower cost and high coverage area. FCD can be obtained by tracking vehicle trajectories individually or by processing multiple tracks anonymously to produce average speed information commercially. For commercial FCD, the spatio-temporal distribution of these vehicles in actual traffic, traffic Penetration Rate (PR) is the most important factor affecting the accuracy of speed estimations, despite the high number of registered vehicles feeding to an FCD provider, denoting the market PR. This study proposes a method for assessing the traffic PR of commercial FCD by evaluating its speed estimation quality compared to Ground Truth (GT) data. GT speed data were employed to generate different levels of traffic PR using Monte Carlo (MC) simulations, which resulted in the development of Quality-PR (Q-PR) relations for Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) as selected Measures of Effectiveness (MoE). Simulation-based FCD results at an urban road segment in Ankara (Turkey) showed that a quality of FCD with traffic PR of 15% or more would improve significantly. Use of the developed Q-PR relations suggested an approximately 5% traffic PR for the commercial FCD speeds at the location.

Keywords: commercial floating car data, floating car data quality, penetration rate, probe vehicle, Monte Carlo simulations.

Notations

Abbreviations:

AAPE – average absolute percentage error;
ASE – absolute speed error;
CI – confidence interval;
FCD – floating car data;
GPS – global positioning system;
GT – ground truth;
ID – identification;
IQR – interquartile range;
LB – lower bound;
LOS – level of service;
MAE – mean absolute error;
MAPE – mean absolute percentage error;
MC – Monte Carlo;
MoE – measures of effectiveness;
MRE – maximum relative error;
NGSIM – next generation simulation program;
NMFD – network macroscopic fundamental diagrams;
OD – origin–destination;
PR – penetration rate;
Q-PR – quality-PR;
RMSE – root mean square error;
RTMS – remote traffic microwave sensor data;
TMC – traffic message channel;
TT – travel time;
UB – upper bound.

Variables:

K – set of MC simulation runs;
k – MC simulation run;
$MAPE_u$ – average MAPE between GT and FCD speed [%];
$\overline{MAPE_u}$ – MAPE between GT and FCD speed [%];
$MAPE_{u,\max}$ – max MAPE between GT and FCD speed [%];
$MAPE_{u,\min}$ – min MAPE between GT and FCD speed [%];
$MAPE^{\delta}_{u,k}$ – $MAPE_u$ in kth MC simulation, $k \in K$ for PR δ;
$MAPE^{\delta}_{u,\max}$ – max $MAPE_u$ in K simulations for PR δ;
$MAPE^{\delta}_{u,\min}$ – min $MAPE_u$ in K simulations for PR δ;

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$MAPE^{\delta}_{u,LB}$ – LB of $MAPE_u$ in K simulations, for PR δ;
$MAPE^{\delta}_{u,UB}$ – UB of $MAPE_u$ in K simulations, for PR δ;
$\overline{MAPE_u}^{\delta}$ – average of $MAPE_u$ in K simulations for PR δ;
g^t – minute-based flow at time t, $t \in T$ (GT);
T – analysis time period of the GT data;
t – sampling interval for FCD (1 min);
u_i^t – spot speed of a vehicle i observed in minute t, $t \in T$ (GT);
$\overline{u}^t$ – space mean speed at time t, $t \in T$ (GT);
$\overline{u}^t_{FCD}$ – average speed from FCD at time t, $t \in T$;
$\hat{u}^t_{FCD,k}$ – simulated FCD speed from kth MC simulation at time t, $t \in T$;
δ_u – PR in MC simulation in GT speed data;
δ – traffic PR based on GT flow data;
$\hat{\delta}^{FCD}$ – estimated traffic PR [%] for commercial FCD;
$RMSE_u$ – RMSE between GT and FCD speed [km/h];
$\overline{RMSE_u}$ – average RMSE between GT and FCD speed [km/h];
$RMSE_{u,\max}$ – max RMSE between GT and FCD speed [km/h];
$RMSE_{u,\min}$ – min RMSE between GT and FCD speed [km/h];
$RMSE^{\delta}_{u,k}$ – $RMSE_u$ in kth MC simulation, $k \in K$ for PR δ;
$RMSE^{\delta}_{u,\max}$ – max $RMSE_u$ in K simulations for PR δ;
$RMSE^{\delta}_{u,\min}$ – min $RMSE_u$ in K simulations for PR δ;
$RMSE^{\delta}_{u,LB}$ – LB of $RMSE_u$ in K simulations, for PR δ;
$RMSE^{\delta}_{u,UB}$ – UB of $RMSE_u$ in K simulations, for PR δ;

Introduction

Urban traffic monitoring requires traffic data, which are traditionally obtained from various sources, such as loop detectors, point sensors and video cameras. Although these sources provide highly reliable data in occupancy, average speed or flow measurements, their instalment and maintenance costs make them more difficult to implement at many locations along urban roads, which is even more challenging for local authorities due to budget limitations. On the other hand, FCD represent a relatively new and cheap traffic data source that provides estimated speed (or TT) data for predefined segments based on individual track data from GPS-equipped vehicles in the network. These vehicles can be specifically probed or fleet vehicles (e.g., taxis and trucks) tracked mainly for other purposes. The location, speed and direction data are sent anonymously to a central processing unit and processed to determine average speeds. FCD in its raw format has detailed vehicle trajectory information allowing one to construct time–space diagrams, which can produce very detailed information about many different traffic conditions (i.e., location of queue joins or exit, acceleration, deceleration, etc.). However, the storage and processing of this extensive amount of data is very challenging. To ease the use of FCD, spatiotemporal averaging is employed to obtain speed for predefined segments of the road network as in commercial FCD, provided for many regions and countries by private companies, such as INRIX, TomTom, HERE and Be-Mobile. The extensive coverage area of these data makes them preferable, particularly in developing countries, where urban regions face exacerbated traffic congestion on major arterial roads.

Many studies have focused on the estimation of traffic speed and state using both FCD with GPS-equipped vehicle trajectories and commercial FCD; the results have demonstrated acceptable errors in speed and traffic state estimation. An increase in the number of GPS-equipped vehicles in the future is a promising factor encouraging the use of FCD for urban arterial management purposes; however, FCD PR is still a crucial issue in the quality of traffic parameter estimations, whether defined as reliability, accuracy or otherwise. Market PR for FCD is mostly stated as a constant rate based on the registered number of GPS-tracked vehicles; for example, among the 19+ mln registered vehicles in Turkey, approximately 600000 GPS-equipped vehicles are feeding to FCD, reaching a market PR of 3%. However, this figure may be misleading because the spatio-temporal distribution of these vehicles on arterial roads over a 24 h period can vary significantly due to traffic demand and conditions. Traffic PR δ, defined as the sampling percentage of GPS-equipped vehicles in traffic volumes, has been addressed as a key issue in FCD studies with individual probe vehicle data.

Since commercial FCD utilized both real time and historical data information, its PR has not been studied so far, representing a gap in assessing its reliability as a traffic data source, which is the main goal of this study. To our best knowledge, there is no published research methodology that allows one to estimate the PR of commercial data independently. This research proposes a novel methodology to estimate the FCD traffic PR at a location based on GT traffic data (speeds and flows). GT speed data were used to generate randomly simulated FCD speeds with different traffic PRs δ, using the MC technique. Using commonly selected quality evaluation parameters of MAPE and RMSE, Q-PR relations of FCD were developed, which were later used to draw insights regarding the existing traffic PR of FCD, $\hat{\delta}^{FCD}$ at the study location. The method was applied for an urban corridor segment in Ankara (Turkey) for which 1 min commercial FCD speeds were available, and the analysis was repeated for different time periods – am-peak, off-peak and whole-day, which also showed the sensitivity of the method to observation period and traffic regimes.

1. Literature review

In the literature, the phrase FCD is used to refer to time-stamped location and speed data collected from vehicles. In their raw format, FCD provide detailed vehicle trajectory information (Type 1). It can be obtained from either simulation environment (Type 1a) or real probe vehicles flowing on the roads (Type 1b). Thus, it could be possible to construct time–space diagrams that can produce highly detailed information about many different traffic conditions (e.g., location of queue joins or exit, acceleration and deceleration). However, the storage and processing of this extensive amount of data is particularly challenging. To ease the use of FCD, spatio-temporal averaging is employed to obtain speeds for predefined segments of the road network as in commercial FCD (Type 2). Due to considerable time and effort being saved, commercial FCD is quite advantageous for the monitoring and planning of urban networks. Thus, it is important to review the FCD literature for these 2 types of data – Type 1 and Type 2 – separately (see Table 1 for literature overview). It should be noted that FCD are mostly collected from commercial vehicles (taxis, public transit vehicles, delivery vehicles, etc.). Therefore, there is potential for bias in vehicle sampling. Despite this sampling bias, it is widely accepted that FCD provide valuable information when sampled vehicles follow the traffic flow and traffic PR is sufficiently high. However, not all FCD studies focus on the issue of PR, which can affect the reliability of the extracted traffic information. Thus, the FCD literature is reviewed from this perspective as well.

1.1. Overview of FCD studies

Studies using probe vehicles (Table 1) mostly map vehicle trajectories to the road network to produce estimates for traffic state parameters, i.e., TT in researches by Chen, Chien (2000), Cetin *et al.* (2005), Jenelius, Koutsopoulos (2015), He *et al.* (2019a); speed in researches by Cheu *et al.* (2002), Hong *et al.* (2007), Klunder *et al.* (2017), or congestion-related attributes such as, location of an incident in research by Kerner *et al.* (2005); congestion duration and location in researches by Kerner *et al.* (2005), Vandenberghe *et al.* (2012), and queue length in research by Ramezani, Geroliminis (2015). Alternatively, FCD-based fundamental diagrams are developed at the link or network level, referred to as NMFD, recently in researches by Sunderrajan *et al.* (2016); Ambühl, Menendez (2016); some of these studies used simulated vehicles in researches by Chen, Chien (2000), Cetin *et al.* (2005), Jenelius, Koutsopoulos (2015). Alternatively, simulated vehicle trajectories were also produced based on real ones using a NGSIM as in researches by Ramezani, Geroliminis (2015), He *et al.* (2019b).

Using real taxi fleet trajectory data from Stockholm (Sweden) with 1500 taxis, Jenelius, Koutsopoulos (2013) examined the reliability of TT estimation in the absence of traffic flow data along a 1.4 km urban arterial stretch (with 26 intersections, 10 of which were signalized). The results suggested that TT estimation can be achieved using low traffic PR. Using taxi fleet data from Nanjing (China) with 7700 taxis, Yun, Qin (2019) investigated the TT reliability of FCD along a 3.1 km road stretch (between 5 intersections); the existing traffic PR was found to be adequate in terms of 15 min TT reliably. Brockfeld *et al.* (2007) utilized a taxi-based FCD for a 2 km urban corridor in Nuremberg (Germany), showing that FCD had significant potential for congestion detection, but short-term speed drops were not captured. He *et al.* (2019b) focused on identifying turn-level intersection congestion along 5 ring roads in Beijing (China) (with almost 4000 intersections) using GPS-equipped taxi fleet data; the results demonstrated the substantial potential of the approach. Based on speed from taxi fleet data and flow from loop detectors, Beibei *et al.* (2016) developed NMFD for a 2 km^2 area in Changsa (China), showing the potential use of FCD fusion with another traffic data source. Integration of conventional surveys with big data has also paid more attention for travel demand analysis (Cascetta 2009; Grengs *et al.* 2008; Ribeiro *et al.* 2014; Nigro *et al.* 2018; Croce *et al.* 2019). Grengs *et al.* (2008) discussed the advantages of FCD for travel demand analysis by comparing conventional travel surveys. Ribeiro *et al.* (2014) integrated FCD with household survey data to establish travel behaviour in Porto Alegre (Brazil). It was found that FCD provided more reliable and precise data compared to traditional surveys. Nigro *et al.* (2018) stated that OD TTs from FCD were found to be more reliable in Roma (Italy) as well. Croce *et al.* (2019) used taxi fleet data in combination with traditional household travel surveys to derive travel behaviour in the Province of Calabra (Italy); despite the challenges in FCD quality, the method was found to be considerably useful for the development of transportation system models.

Based on commercial FCD with 3 min intervals from 2 selected corridors in Roma (Italy), De Fabritiis *et al.* (2008) proposed a neural network based model to estimate the average link speeds and to determine the congestion locations. They reported successful speed prediction for 15 and 30 min periods. Houbraken *et al.* (2018) focused on the use of commercial FCD for dynamic traffic management for the A27 highway section in Gorinchem (Netherlands), and showed success in capturing queue formations and dissipations. Using commercial FCD speed data (INRIX company) from Beijing (China) fused with RTMS, Zhao *et al.* (2009) analysed the traffic flow characteristics on ring road expressways to derive a fundamental diagram. With similar FCD data in Raleigh, Durham and Chapel in North Carolina (US), Chase *et al.* (2012) fused FCD speed with RTMS data to obtain a speed-flow fundamental diagram, but due to systematic errors and low PRs of commercial FCD, the desired speed-flow relation could not be obtained. Altintasi *et al.* (2017) focused on the detection of recurrent congestion or bottleneck locations and even the length of queues formed before the bottlenecks. In follow up studies, Altintasi *et al.* (2019a, 2019b) evaluated success of the commercial FCD in:
- derivation of the traffic fundamental diagram as fused with GT speeds;
- determination of transformation functions relating the FCD speeds with the GT ones;
- estimation of speed and LOS values;
- dominant traffic states by analysing longer duration of FCD achieves;
- queue formations and dissipations around bottleneck locations.

1.2. PR coverage in FCD studies

Although there are many studies focusing on applications of FCD, the effects of traffic PR of FCD were not addressed in all of them, as shown in Table 1. In some of the studies, an overall market PR was calculated from the ratio of FCD-probed vehicles to the vehicle park in the same region. There is a wide range of reported market PR for commercial FCD; 5% in Beijing (China) (He *et al.* 2019a, 2019b), 6…7% in Changsa (China) (Beibei *et al.* 2016) and 2% for Calabra (Italy) (Croce *et al.* 2019). De Fabritiis *et al.* (2008) stated a particularly low market PR of 1.7% for commercial FCD in Italy, but Houbraken *et al.* (2018) claimed a market PR of 6…8% for Amsterdam (Netherlands). Many studies examined the effect of traffic PR on TT. Chen, Chien (2000) suggested a minimum of sampling rates for congested conditions and uncongested conditions, separately. Jenelius, Koutsopoulos (2015) further investigated the probe vehicle data sampling either by time or space for TT estimation and proposed a sampling procedure for different conditions. He *et al.* (2019a, 2019b) indicated that a 4% traffic PR with 20 sec sam-

Table 1. Overview of probe vehicle based (Type 1) and commercial (Type 2) FCD studies

Study	FCD coverage		MoE	
	used for	PR comments	MoE	comments
Type 1a: studies using simulated FCD				
Chen, Chien (2000)	TT	6…12.5% traffic PR needed	MRE	5% MRE
Cetin *et al.* (2005)	TT	–	–	–
Jenelius, Koutsopoulos (2015)	TT	–	–	–
He *et al.* (2019a, 2019b)[1]	TT	<10% traffic PR in NGSIM[1] data	MAPE	4% traffic PR produced MAPE as 6.1…12.9%
Cheu *et al.* (2002)	speed	minimum 6% traffic PR needed	MAE	5 km/h of MAE for 15% traffic PR
Hong *et al.* (2007)	speed	minimum 2% traffic PR needed	RMSE	significant decrease after 20% traffic PR
Klunder *et al.* (2017)	speed	minimum 10% traffic PR needed	AAPE	10% traffic PR produced 5.6% AAPE
Kerner *et al.* (2005)	congestion	1.5…2.0% traffic PR needed for incident location detection	–	–
Vandenberghe *et al.* (2012)	congestion	traffic PR needed: highway (1% –10 sec), urban (10% – 1 sec)	–	–
Ramezani, Geroliminis (2015)[1]	queue length	<10% traffic PR in NGSIM data; 20% traffic PR needed	MAE	queue length error of 2…4 veh
Sunderrajan *et al.* (2016)	NMFD	minimum 5% traffic PR needed	–	–
Ambühl, Menendez (2016)	NMFD	minimum 3% traffic PR needed	–	–
Type 1b: studies using real FCD with vehicle trajectory data				
Jenelius, Koutsopoulos (2013)[*]	TT	–	–	–
Yun, Qin (2019)[*]	TT	minimum 10% traffic PR	MAPE	10…14% MAPE
Brockfeld *et al.* (2007)[*]	congestion	–	–	–
He *et al.* (2019a, 2019b)[*]	congestion	market PR in Beijing (China) (5%)	–	–
Beibei *et al.* (2016)[*]	NMFD	market PR in Changsa (China) (6…7%)	RMSE	flow error of 38.22 veh
Grengs *et al.* (2008)	OD matrix	–	–	–
Ribeiro *et al.* (2014)	OD matrix	–	–	–
Nigro *et al.* (2018)	OD matrix	market PR in Roma (Italy) (2.5%)	–	–
Croce *et al.* (2019) [*]	OD matrix	market PR in Calabra (Italy) (2%)	–	–
Type 2: studies using commercial FCD				
De Fabritiis *et al.* (2008)	speed	market PR in Italy (1.7%) and higher in Rome (2.4%)	MAPE, RMSE	RMSE of 7…9 km/h, MAPE of 2…8%
Altintasi *et al.* (2019a, 2019b)	speed, congestion	market PR in Turkey (3%)	–	–
Houbraken *et al.* (2018)	congestion	6…8% market PR in the Netherlands	–	–
Zhao *et al.* (2009)	NMFD	–	–	–
Chase *et al.* (2012)	NMFD	–	–	–

Notes: "–" stands for "not addressed"; [1] – using NGSIM; [*] – FCD is based on taxi fleet data.

pling frequency was necessary for TT estimation. Yun, Qin (2019) reported that 10% traffic PR was required for reliable TT estimation. For the speed prediction studies, Cheu *et al.* (2002) performed simulation-based analysis under various traffic volumes, suggesting at least 6% traffic PR; however, a significant improvement in the accuracy of speed estimation was observed for a PR of 15%. Klunder *et al.* (2017) showed that for 1% PR, there were high levels of error, whereas 10% PR generated acceptable results. Hong *et al.* (2007) proposed a minimum 2% traffic PR for speed estimation. For congestion applications, Kerner *et al.* (2005) investigated the minimum traffic PR required, which suggested 1.5% PR for detection of an incident location with a 65% probability; on the other hand, Vandenberghe *et al.* (2012) proposed at least 1% PR (with a 10 sec sampling interval). Brockfeld *et al.* (2007) emphasized an insufficient PR of the study region without discussing the existing traffic PR. For queue length estimation near signalized intersections from probe vehicle data, Ramezani, Geroliminis (2015) proposed a model with varying PR and a sampling frequency in an NGSIM environment: a PR of 20% (with 40 sec sampling frequency) produced a MAE of 4 vehicles, which was reduced to 2 vehicles with 50% PR.

To derive NMFD, Sunderrajan *et al.* (2016) created various scenarios with different PRs for a simulated highway corridor; a minimum PR of 5% was estimated for NMFD derivation. Ambühl, Menendez (2016) proposed a data fusion algorithm using FCD and loop detector data for deriving the NMFD for the city of Zurich, concluding that a minimum PR of 3% was required for FCD. Beibei *et al.* (2016) also utilized real loop detector data and taxi probe vehicle data to build an NMFD, in which heterogeneous traffic PR of taxis was observed between 6…7%.

1.3. MoE in FCD studies

When quantifying the success of FCD, some studies used MoE determined by comparing FCD-based estimated values with GT values. The different MoE used by FCD studies in Table 1 included:

- MRE (Chen, Chien 2000);
- MAPE (De Fabritiis *et al.* 2008; He *et al.* 2019a, 2019b; Yun, Qin 2019);
- RMSE (De Fabritiis *et al.* 2008; Beibei *et al.* 2016);
- MAE (Cheu *et al.* 2002; Ramezani, Geroliminis 2015);
- AAPE (Klunder *et al.* 2017).

For the use of FCD TT in the development of NMFD for a region in Changsa (China), despite the overall taxi penetration in the study region being monitored for every sampling interval, only RMSE in estimated flow values was measured as an indicator of FCD quality (Beibei *et al.* 2016). Similarly, while monitoring the traffic PR of taxi numbers along 4 consecutive urban road segments, the quality of average TT estimation was measured as 10…14% (Yun, Qin 2019). In the case of FCD quality in speed estimation in Rome (Italy), an RMSE of 7…9 km/h was reported, for which a MAPE range of 2…8% was observed for a market PR of 2.4% (De Fabritiis *et al.* 2008). Note – despite the existence of a broader literature on the quality of FCD-based estimations, studies that report/discuss FCD PR only are included in Table 1 for the focus of PR discussion.

While evaluating the quality of FCD in traffic parameter estimations based as a function of PR of FCD in simulated environments, for a 5% MRE level, 6% traffic PR was required for uncongested regimes, whereas 12.5% PR was necessary for congested cases (for volume/capacity rates of 0.82) (Chen, Chien 2000). Another TT estimation quality evaluation showed a minimum of 4% traffic PR resulted for an MAPE of 6.1…12.9% (He *et al.* 2019a, 2019b). In speed estimations, 15% traffic PR generated 5 km/h MAE (Cheu *et al.* 2002), whereas an AAPE of 5.6% was reported for 10% traffic PR (Klunder *et al.* 2017). For NMFD derivation, Beibei *et al.* (2016) found an RMSE of 38.22 veh as a reliability indicator for 6…7% market PR in Changsa (China). In the estimation of queue lengths with FCD, 2…4 veh were reported as the MAE as an accuracy indicator (Ramezani, Geroliminis 2015).

1.4. Aspects affecting FCD quality

Whether referred to as quality (Cetin *et al.* 2005; De Fabritiis *et al.* 2008; Vandenberghe *et al.* 2012; Ambühl, Menendez 2016; Klunder *et al.* 2017; Houbraken *et al.* 2018; Yun, Qin 2019), accuracy (Ramezani, Geroliminis 2015) or reliability (Sunderrajan *et al.* 2016; Beibei *et al.* 2016), the success of FCD used in estimating traffic state is an important issue for the future of FCD as a traffic data source. For probe vehicle trajectory-based FCD, the crucial point is the representativeness of the probe vehicles in the traffic. GPS trajectories from vehicle fleets (taxis, bus, commercial ones, etc.) may show characteristics different than the average traffic conditions in terms of speeding, dwelling, etc., as well as route choices. This biasedness may be reduced when a mixed set of vehicles are used as probes, such as trajectory data fed into commercial FCD providers. However, there is still the issue of the spatio-temporal distribution rate of these probe vehicles, traffic PR of FCD, affecting the quality of commercial FCD parameters (speed or TT). If all the vehicles were monitored, as in simulated full autonomous/connected vehicle systems (100% market and traffic PRs), such commercial FCD would be simply the GT data, itself. However, a study on the required traffic PR for connected vehicles showed that 15% PR is adequate for estimating space mean speed, which is used in macroscopic traffic flow models (Talebpour, Mahmassani 2016). Even so, there is always the issue of time aggregation (also termed sampling interval) that leads to an averaging of speed (or TT); if FCD values were obtained for 5 min periods, it would convey less realistic values than shorter time aggregations (i.e., 1 min, 30 sec or even 0.1 sec in studies using NGSIM data); this aspect was discussed in the simulation-based FCD studies of (Ramezani, Geroliminis 2015; He *et al.* 2019a, 2019b).

Similarly, aggregation over space, which raises the issue of segmentation in FCD (Jenelius, Koutsopoulos 2015), is another aspect that has to be considered in the evaluation of FCD parameters to represent real traffic conditions. Commercial FCD speeds are mostly provided for segments following the TMC, varying from 500 to 1600 m. Additionally, improved FCD segments with shorter lengths (up to 220 m) providing more consistency with the road network topology were introduced by INRIX (2018). Even a finer segmentation with lengths of up to 100 m for approaches at signalized urban arterials was created by the TomTom company for urban roads in Munich (Germany) (Kessler *et al.* 2018).

The current market PR of FCD, however, is far from the ideal full market PR levels; thus, the quality of FCD parameters is affected by all of the aforementioned aspects to a significant degree, in addition to the issue of use of archival data or short-term history, which is employed when sparse probe vehicle conditions are observed. In studies using real vehicle trajectory FCD data, the FCD sparsity was addressed by developing a historical TT database (Jenelius, Koutsopoulos 2013) or aggregation of FCD over 15 min (Yun, Qin 2019). Zhang *et al.* (2015) proposed a model to estimate the FCD traffic PR of a single road segment in Beijing ring roads, based on which a statement of need for higher PR values over longer segments was made, but, without any numerical support.

The review of the FCD literature from the perspective of PR has shown that there was a wide range of estimations for the sufficient PR for a selected FCD application success (estimation of speed, TT, queue length, NMFD, etc.). This rate may change between road types (highway versus urban) as well as congestion levels. Furthermore, it may be different for various sampling intervals and segment length. Although some simulation studies have provided MoE as a function of PR, the majority of them failed to associate FCD traffic PR to quality (Q-PR), due to its complex nature in space and time and its correlation between the estimated parameters. It is even more challenging in the case of commercial FCD and its reliability in urban traffic management and planning, which has a much lower market PR than the desired minimum levels, currently. As a result, none of aforementioned studies focused on the estimation of traffic PR of commercial FCD, it was not evaluated so far, which is a gap in literature and the main motivation of this research.

2. Methodology

2.1. Commercial FCD at the study location

Commercial FCD used in this study included average speed published at 1 min time intervals dynamically. The invariant portion of the data including segment ID, length, posted speed limit, etc., was shared in a static table, in which segment ID was used as the parameter connecting the static and dynamic parts. The corridor Dumlupınar Boulevard (from Hacettepe University interchange to Bilkent University entrance) in Ankara (Turkey) (Figures 1a, 1b), was selected as a major arterial in the form of a multilane urban highway corridor, with three lanes in each direction. The study corridor consists of 82 FCD segments, which have a fine segmentation with a maximum length of 50 m and 1 min time intervals (Figure 1c), and GT was available clearly for Segment 57 (Figure 1d). The speed limit of the corridor is 82 km/h for passenger cars and 70 km/h for commercial vehicles. Note: a preview of FCD speed values for the corridor showed suggested a truncation at the "posted speed limit", a common practice in the commercially available FCD to avoid any use of "voluntarily shared GPS track data of probe vehicles" in speed enforcement, which had previously occurred and received a negative reaction from vehicle owners (Waterfield 2011). Despite higher values than may be observed in real life, a commercial FCD provider published a $\overline{u}_{FCD}^{t} \leq 70$ km/h in the study corridor.

2.2. GT data collection

To collect GT data, a video camera was installed at a high-rise building along the FCD study corridor for one day (25 (Tuesday) October 2016), as shown in Figure 1d. The video camera view provided clear visibility of the study segment of (*length* = 49.15 m) for all three lanes. The analysis time period T, was 07:30 to 16:00 and included the am-peak and noon off-peak hours. Using a MATLAB (*https://www.mathworks.com*) code, the video camera was processed manually to obtain values of (1) 1 min traffic flow g^t and (2) average speed $\overline{u}^t$. The flow was determined by counting vehicles crossing a virtual line at Location 1 in Figure 1d.

For speed detection, a sampling approach was employed to calculate average speeds for every sampling interval t, as follows. For every sampled vehicle i entry and exit times were recorded at Locations 1 and 2, respectively. Individual spot speed of the vehicles u_i^t were averaged to obtain GT speeds $\overline{u}^t$ (Figure 2). The overall GT speed profile of the study segment is illustrated in Figure 1e. Notes: vehicles on each lane were sampled separately, but joined together for the average speed estimations for the segment. Because detecting a sampled vehicle required tracking of the vehicle i between the two observation points, the next vehicle for speed data, vehicle i + 1, was selected as the first vehicle observed at Location 1, after vehicle i passed at Location 2. This approach caused lower sampling rates for speed (labelled as "observed speed volume" in Figure 3), which also had different sampling rates under varying traffic conditions (this issue will be discussed in the PR estimation sections below). Because $\overline{u}_{FCD}^{t}$ were provided at 1 min time intervals, flow and average speed from GT data were compiled for every 1 min period as well. Further, because the traffic data were collected only for a short segment length, no surpassing manoeuvres between lanes were detected during the data collection period. Thus, it was not considered for this study.

Figure 1. The border of the Ankara city and location of the Dumlupınar Boulevard (a, b); FCD segmentations and study segment on Dumlupınar Boulevard in Ankara (Turkey) (c, d); speed profiles of the commercial FCD and GT data at the study segment as well as the outliers in commercial FCD (e)

2.3. Data pre-processing

The extreme values in FCD speed can significantly affect the traffic PR of commercial FCD. To minimize the impact of FCD speed-related problems in the quality evaluation, extreme values in FCD were filtered, and a cleaned-up data set was created (Figure 2). To identify the extreme values, several methods are proposed such as IQR score, *z*-score, box plots, clustering techniques, visualization tools etc. In this study, upper and lower limits for the FCD speed filter were determined by analysing the distribution of the ASE – $ASE^t = \left| \bar{u}^t_{FCD} - \bar{u}^t \right|$ defined for each time $t \in T$. A tolerance upper limit was chosen by simply assuming two folds of the IQR for the ASE to create an upper limit for tolerance in the errors as:

$$ASE_{tolerance} = Q_3 + c \cdot \left(IQR \right), \qquad (1)$$

where: c is a constant value (1.5…2.0, depending on the quality of the analysis); $IQR = Q_3 - Q_1$, in this equation Q_3 and Q_1 represent the 75- and 25-percentile values, respectively. FCD speeds with ASE larger than the tolerance were filtered out.

To determine the appropriate constant value, speed profiles of the commercial FCD and GT data at the study segment was drawn (Figure 1e) and outliers were identified based on the different constant c values of 1.5, 1.7 and 2.0. It was concluded that no significant changes were observed with the varying constant value. In addition to the detected outliers for $c = 2.0$, only two additional outliers were detected for the off-peak and am-peak, separately while selecting the value $c = 1.7$. When $c = 1.5$, additional one outlier was detected at am-peak hour, only (Figure 1e). Thus, any value between 1.5…2.0 can be selectable and it was taken as 2.0 in this study. FCD speeds with ASE larger than the tolerance were filtered out.

2.4. Traffic PR estimation approach for commercial FCD

This study proposed a novel methodology to indirectly estimate the traffic PR of commercial FCD using GT data from a fixed location. The model can be applicable whenever the GT and commercial FCD speed data are available for the road segment located in urban arterial, freeways, highways, etc., to estimate traffic PR at a selected location. The framework of the proposed methodology is given in Figure 2.

As a traffic parameter, commercial FCD provide average speed $\overline{u}^t_{FCD}$ for each time (sampling) interval (see Notations). The proposed methodology for the evaluation of traffic PR has three main stages (Figure 2): (1) GT data collection; (2) generation of simulated FCD with varying traffic PR levels via a MC simulation approach to obtain a Q-PR relation for simulated FCD and (3) estimation of traffic PR of commercial FCD at the road segment. MoE for Q-PR were selected as MAPE and RMSE. The quality of FCD under varying PRs was evaluated by creating various FCD subsets from GT speed dataset u^t_i using MC simulations (Figure 2). In this approach; for each selected PR δ in every simulation MC scenario *k*; a randomly selected speed subset was created u^t_i for each sampling interval *t* and the average of the selected speeds was used to obtain "simulated FCD speed" $\hat{u}^t_{FCD,k}$ for every min *t*. Simulated FCD speeds $\hat{u}^t_{FCD,k}$ were compared with $\overline{u}^t$ values to calculate MoEs, $MAPE^{\delta}_{u,k}$ and $RMSE^{\delta}_{u,k}$.

Generation of simulated FCD speeds and Q-PR relations under varying PRs

In this study, 6 different PRs were selected as $\delta_u = \{5\%, 10\%, 15\%, 25\%, 35\%, 50\%\}$ based on sampled speed data. Randomly generated MC simulations (k = 20) were created

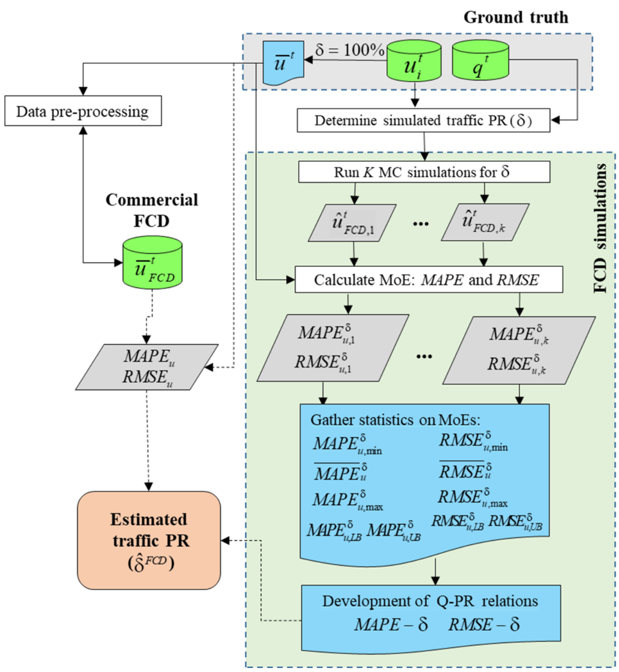

Figure 2. Methodology framework for estimation of traffic PR for commercial FCD-based on Q-PR relations from MC simulations

for each PR δ_u in speed observations. To provide an idea regarding the size of the dataset in the simulated FCD scenarios, a 1 min based number of vehicles with speed data for $\delta_u = \{5\%, 15\%, 35\%\}$ were plotted in addition to all of the speed dataset (δ_u = 100%) in Figure 3. Note: MC scenarios were created based on the observed speed dataset; the corresponding traffic PR δ for an MC scenario, was determined as a function of δ_u as shown in Table 2. For example, for the whole-day analysis, for δ_u = 5% PR MC scenario, the total number of vehicles with speed data was 3.49% (δ) of the total traffic flow for the whole-day analysis period. However, traffic PRs during the peak-hour and off-peak periods were δ = 2.21% and δ = 3.77%, respectively, for the same δ_u.

At the end of the *K* simulations, statistics of MoEs were derived to obtain values of (1) average ($\overline{MAPE}^{\delta}_{u}$, $\overline{RMSE}^{\delta}_{u}$); (2) minimum ($MAPE^{\delta}_{u,\min}$, $RMSE^{\delta}_{u,\min}$) and (3) maximum ($MAPE^{\delta}_{u,\max}$, $RMSE^{\delta}_{u,\max}$). Furthermore, LB ($MAPE^{\delta}_{u,LB}$, $RMSE^{\delta}_{u,LB}$) and UB ($MAPE^{\delta}_{u,UB}$, $RMSE^{\delta}_{u,UB}$) of the MoEs were determined for 95% CI. The same process was repeated for each selected δ. Plotting calculated MoEs versus traffic PR rates (δ) in the simulated scenarios, a set of Q-PR functions were derived. In the third stage of the proposed methodology, $MAPE_u$ and $RMSE_u$ of commercial FCD were calculated by comparing $\overline{u}^t$ and $\overline{u}^t_{FCD}$, which were later used to estimate traffic PR of commercial FCD, $\hat{\delta}^{FCD}$, at the study location from developed Q-PR functions.

2.5. MoE for quality evaluation

Based on the MoEs commonly used in the FCD literature, the following ones were selected:

»» MAPE as proposed in researches by Wang *et al.* (2014), Hu *et al.* (2016) and determined as:

$$MAPE_u = \frac{1}{T} \cdot \sum_{t=1}^{T} \left| \frac{\overline{u}^t_{FCD} - \overline{u}^t}{\overline{u}^t} \right| \cdot 100\,; \tag{2}$$

»» RMSE proposed in research by Wang *et al.* (2014) and calculated as:

$$RMSE_u = \sqrt{\frac{1}{T} \cdot \sum_{i=1}^{T} \left(\overline{u}^t_{FCD} - \overline{u}^t \right)^2}, \tag{3}$$

where: *T* shows the analysis period in terms of [min].

2.6. Limitations of the study

Despite its capability to draw insights about traffic PR at a given location, the proposed approach has the following shortcomings: Because there is no published information regarding how the archival data are used in commercial FCD, which is a common practice for road segments or time periods with missing or limited number of observations, no archival data were assumed in the simulated FCD speeds. Thus, the use of the developed Q-PR relations, which included only PR-based errors, may produce different PR rates, if commercial FCD have a strong ar-

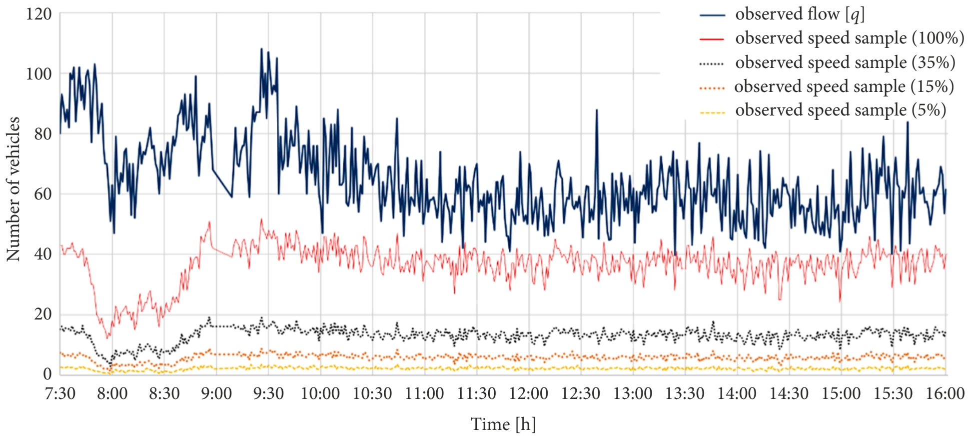

Figure 3. GT speed and flow observation data with average number of speed samplings for 1 min simulated FCD via MC simulations

Table 2. δ_u and corresponding δ values for different analysis periods

δ_u [%]	δ [%]		
	whole-day	am-peak	off-peak
5	3.49	2.21	3.77
10	6.38	4.06	6.88
15	9.27	5.93	10.00
25	15.10	9.59	16.30
35	20.91	13.27	22.57
50	29.59	18.73	31.96

chival data usage. As an alternative, Q-PR relations can be obtained for simulated FCD scenarios with assumed archival data usage with known principles. Secondly, the GT data were not collected at multiple locations and/or for different FCD segment lengths, which is necessary to generalize the use of derived Q-PR relations. Segmentation of the road network is also critical to discuss the length of validity of the results: in intercity roads, traffic conditions and PR values could be estimated for longer stretches, as there are few entry/exit points. But, in urban road networks, due to existence of many crossing roads and varying traffic conditions (i.e., traffic signals, stops, etc.), much shorter analysis distances must be taken for FCD generation (i.e., INRIX company provided 220 m length road segments for uninterrupted arterials while 100 m length for signalized ones). Thus, this requires more locations to be monitored to have a more network based traffic PR estimations.

Thirdly, using 1 min FCD speeds, which are commercially available surely brings some limitations in estimation of certain traffic conditions (detection of congestion formation, etc.), but, its effect on estimation on traffic PR values is not expected to be that strong for the following reasons. Vehicle-based traffic events (slowing downs, speeding up, traffic signal phases, etc.) can be observed in shorter time intervals (i.e., in 15 or 30 sec data aggregations) and finer FCD time aggregations can be crucial to capture them as in studies with NGSIM and real vehicle trajectory data. It is crucial and necessary for individual vehicle level decision making such as autonomous and connected vehicles operations. Such data encompasses very detailed information providing space-time position of the vehicles for every second; thus, location of queue joins or exit, acceleration, deceleration, information can be derived. However, the storage and processing of this extensive amount of data is very challenging. That is why spatiotemporal averaging is employed to obtain average speed for predefined segments of the road network like in commercial FCD. Even though the individual vehicle information is lost, such data is useful for overall network traffic management and analysis such as ID of the recurrent congestion locations, queue formations and dissipations, incident/bottleneck locations and traffic state estimations. Therefore, for the overall urban traffic monitoring 1 min average speed data can be more cost effective due to aforementioned reasons. Thus, we could not evaluate the limitation that the commercial FCD speed with 1 min time intervals imposed.

The use of commercial FCD speed with 1 min time intervals is a more aggregate analysis compared to use of FCD from NGSIM or real vehicle trajectory data obtained from taxi fleets. While it is possible to get more detailed traffic and PR data with the latter, the large-scale of it is very difficult due to data storage problems for large networks. Thus, commercial FCD speeds are produced in longer time intervals; in an attempt to estimate to traffic PR for commercial FCD, this study did not focus on developing Q-PR relations for shorter time aggregations (i.e., 15, 30 sec, etc.), as they would be consistent with the available commercial FCD.

3. Case study results

3.1. GT and FCD speed overview

For the study segment, the profile of the GT speeds showed that sudden reductions were observed after 07:30 until 09:00, indicating the severe congestion that marked the am-peak (Figure 1e). No other congestion was detected until the end of the study period because the evening peak was not observed due to early sunsets in October in Ankara. Outliers in FCD speeds, based on Equation (1), were detected mostly in the uncongested regime, indicating either poor quality of FCD or errors in FCD broadcasting temporarily. To improve the analysis, sources of errors in the commercial FCD other than PR-based ones were eliminated as much as possible, as follows: a filtered FCD speed dataset was created by removing these outliers. Plotting FCD speed profile $\overline{u}^t_{FCD}$ against the GT-based one showed that FCD speeds mostly followed the GT values; however, it underestimated during the off-peak periods and overestimated during the peak period. During the traffic state change from uncongested to congested regime or vice versa, $\overline{u}^t_{FCD}$ did not respond immediately to the sudden decrease/increase in speed, showing a time lag of approximately 4 min. A second round of data processing was performed to eliminate this time-lagging in the commercial FCD by shifting the latter during the am-peak only (Figure 1e).

To evaluate the speed estimation quality of the commercial FCD at the study location, $MAPE_u$ and $RMSE_u$ values were calculated for different analysis periods separately (Table 3). In the whole-day evaluation, $MAPE_u$ and $RMSE_u$ were calculated as 17.22% and 11.67 km/h, respectively. Elimination of the outliers in FCD speeds produced the filtered FCD dataset with reduced $MAPE_u$ and $RMSE_u$ of 13.65% and 8.73 km/h, respectively. Similarly, a RMSE of 9.6 km/h was reported for an urban corridor by Kim, Coifman (2014). For the am-peak, $MAPE_u$ was higher (47.52%), which is most likely due to a lagged response: substantially larger MAPE values for speed (80…209%) were reported for an urban corridor in Hu *et al.* (2016). $RMSE_u$ on the other hand, was calculated as 13.87 km/h. Filtered FCD further reduced $RMSE_u$ and $RMSE_u$ to 36.94% and 11.72 km/h, respectively. Additionally, the elimination of time-lagging in commercial FCD resulted in significant decreases in $MAPE_u$ values from 47.52% to 32.32% during the am-peak for raw FCD (Table 3). The effect of time-lagging on $MAPE_u$ was also observable considering the entire analysis period, for which an almost 2% decrease in $MAPE_u$ was detected. The performance measure values remained constant for the off-peak times because the time lag correction was only implemented for the am-peak. Furthermore, filtered FCD with lag correction produced lower $MAPE_u$ and $RMSE_u$ as 12.76% and 8.30 km/h, respectively for the whole-day period. Slightly decrease in $MAPE_u$ and $RMSE_u$ was also observable in am-peak and off-peak period as tabulated in Table 3.

Despite a stronger relationship during the am-peak ($R^2 = 0.76$), the rather low value of R^2 for the entire analysis was due to small oscillations around the free flow values during the long off-peak periods, which also dominated the whole-day period. Filtering extreme values produced an improved R^2 value of 0.82 for the am-peak, whereas lag correction itself showed an improved value of 0.79 for raw FCD (Table 3); however, a high correlation between the GT and FCD speeds was observed when a filtered and lag-corrected FCD dataset was used ($R^2 = 0.86$).

3.2. Quality of simulated FCD speed

Evaluating the results of 20 MC simulations (randomly created using the GT speed data described in Section 2.4) for each selected δ_u, first, the change of speed R^2 was monitored as shown in Figure 4. As expected, when δ_u was increased, speed R^2 was increased significantly. However, for very low values of δ_u = 5% (which corresponded to δ = 3.49% for the entire study period from Table 2), speed R^2 values reduced significantly to 0.70…0.80. At a 15% PR, these values reached up to the 0.90 level, suggesting a strong estimation power of simulated FCD speeds.

The variations of $MAPE^{\delta}_{u,k}$ and $RMSE^{\delta}_{u,k}$ by PRs in MC scenarios were depicted for the entire analysis period as well as the am-peak separately, as shown in Figure 5. For the entire analysis period (Figures 5a, 5c), with a very low PR of δ_u = 5%, $MAPE^{\delta}_{u,k}$ was 9…11% and $RMSE^{\delta}_{u,k}$ changed to 9…11 km/h. When δ_u was increased to 15%, both error measures decreased significantly. The availability of much higher FCD PRs brought the error measures $MAPE^{\delta}_{u,k}$ and $RMSE^{\delta}_{u,k}$ down (as low as 2% and 2 km/h in δ_u = 50%). During the am-peak, for low PRs (δ_u < 15%), higher fluctuations were observed in $MAPE^{\delta}_{u,k}$ and

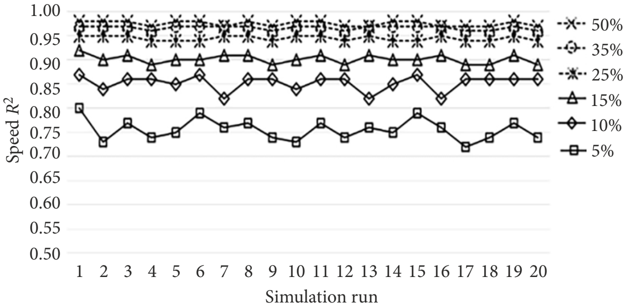

Figure 4. Variation of R^2 performance of MC simulation by PR for speed

Table 3. Commercial FCD speed performance based on $MAPE_u$, $RMSE_u$ and R^2 on the study day

Time period	Raw FCD			Filtered FCD			Raw FCD with lag correction			Filtered FCD with lag correction		
	$MAPE_u$	$RMSE_u$	R^2	$MAPE_u$	$RMSE_u$	R^2	$MAPE_u$	$RMSE_u$	R^2	$MAPE_u$	$RMSE_u$	R^2
whole-day	17.22	11.67	0.45	13.65	8.73	0.68	14.66	11.01	0.47	12.76	8.30	0.71
am-peak	47.52	13.87	0.76	36.94	11.72	0.82	32.32	10.15	0.79	31.29	9.60	0.86
off-peak	11.07	11.17	–	9.03	8.01	–	11.07	11.17	–	9.03	8.01	–

$RMSE^{\delta}_{u,k}$ values as shown in Figures 5b and 5d, respectively. This may be due to the fact that there were limited numbers of observations during the am-peak (Figure 3) in these penetration cases, which may lead to higher variability; thus, higher errors. $MAPE^{\delta}_{u,k}$ values were slightly higher (9…18%) compared to whole-analysis results; however, even with δ_u = 15% penetration, they were reduced to 8% rapidly, in addition to a much desired $RMSE^{\delta}_{u,k} < 5$ km/h level.

At the end of the 20 simulation runs, Kolmogorov–Smirnov test revealed that the distribution of the MoEs for each δ_u was normally distributed with a significance value greater than 0.05. LB and UB of MoEs for 95% CI were depicted for each δ_u showing a linear relation as shown in Figure 6. For the whole-analysis period with low δ_u, $MAPE^{\delta}_{u,LB}$ and $MAPE^{\delta}_{u,UB}$ were around 10% (Figure 6a) while they were slightly higher for the am-peak as 12% and 14%, respectively (Figure 6b). When δ_u = 15%, $MAPE^{\delta}_{u,LB}$ and $MAPE^{\delta}_{u,UB}$ decreased to 6.5% and 6.7% for the whole-analysis and 9.3% to 10.2% for the am-peak, respectively. The variation of the $RMSE^{\delta}_{u,LB}$ and $RMSE^{\delta}_{u,UB}$ with respect to δ_u were also depicted in Figure 6c and Figure 6d, for the whole-analysis and am-peak period, separately.

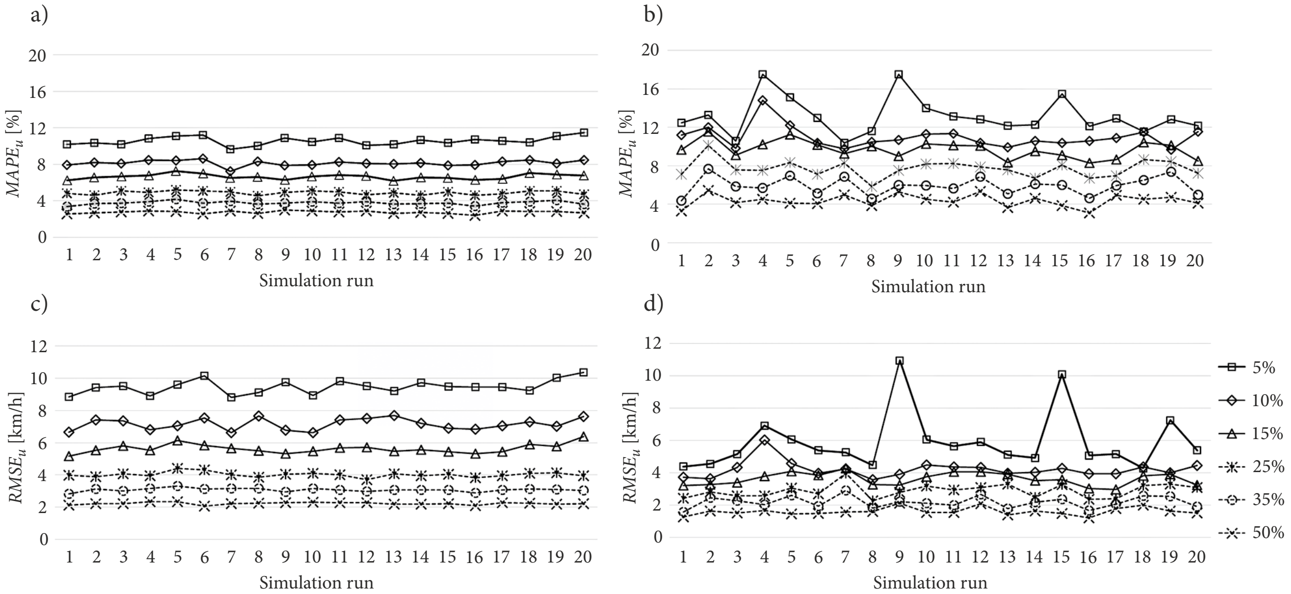

Figure 5. Variation of $MAPE_u$ and $RMSE_u$ performance for MC simulations during whole-analysis period (a, c), am-peak period (b, d)

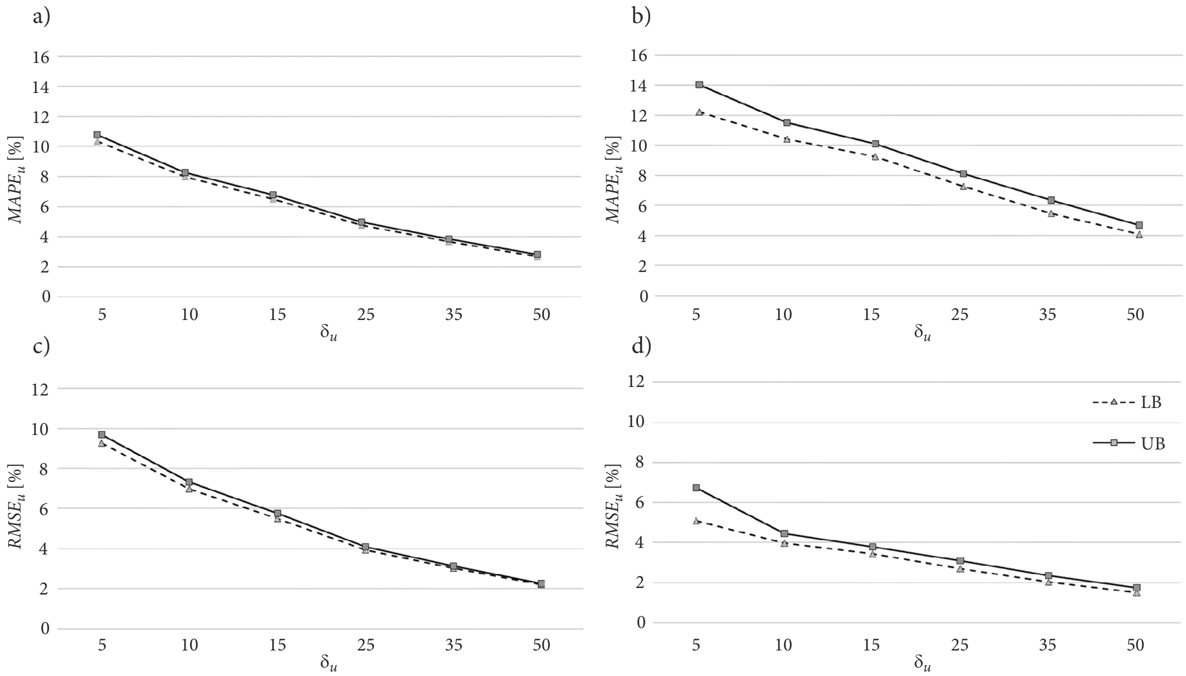

Figure 6. UB and LB of $MAPE_u$ and $RMSE_u$ performance for MC simulations with 95% CI during whole-analysis period (a, c), am-peak period (b, d)

Among 20 MC runs for each scenario, average, maximum and minimum values of $MAPE_u$ and $RMSE_u$ were plotted against the flow-based simulated FCD PRs δ to obtain Q-PR relationships, as shown in Figure 7a. The same procedure was repeated to obtain Q-PR relations for the am-peak and off-peak values (Figures 7b, Figure 7c), as well. The results indicated a strong logarithmic decay between FCD PRs and error measures, for which the analytical relations are provided in Table 4. For the sake of visualization, the Q-PR relations were extrapolated beyond the simulated scenario values in both lower and upper ends.

3.3. Estimating traffic PR in a commercial FCD

Logarithmic Q-PR functions in Table 4 were used to estimate the Q-PR relations at the study location. For example, working with the Q-PR relations for the entire study period (Equations (UW1a), (UW1b) and (UW1c)), putting the observed error values in the left-hand side (Table 3) suggested the following estimated existing PRs for the commercial FCD in the study corridor:

$$17.22\% = MAPE_{u,\max} = -3.944 \cdot \ln(\delta) + 16.128 \rightarrow \delta = 0.76;$$

$$17.22\% = \overline{MAPE_u} = -3.678 \cdot \ln(\delta) + 14.991 \rightarrow \delta = 0.54;$$

$$17.22\% = MAPE_{u,\min} = -3.376 \cdot \ln(\delta) + 13.710 \rightarrow \delta = 0.35,$$

as reported in Table 5. Alternatively, using Q-PR from $RMSE_u$, estimated traffic PR of:

$$11.67 \text{ km/h} = RMSE_{u,\max} = -3.769 \cdot \ln(\delta) + 14.843 \rightarrow \delta = 2.32;$$

$$11.67 \text{ km/h} = \overline{RMSE_u} = -3.421 \cdot \ln(\delta) + 13.514 \rightarrow \delta = 1.71;$$

$$11.67 \text{ km/h} = RMSE_{u,\min} = -3.179 \cdot \ln(\delta) + 12.532 \rightarrow \delta = 1.31,$$

were much higher. Since certain data problems were already detected in the evaluation of the FCD compared to GT, the $\hat{\delta}^{FCD}$ estimations are repeated using both filtered and lag-corrected FCD (with parenthesis), as shown in Table 5. $\hat{\delta}^{FCD}$ was estimated as 2.35% and 5.67% in the

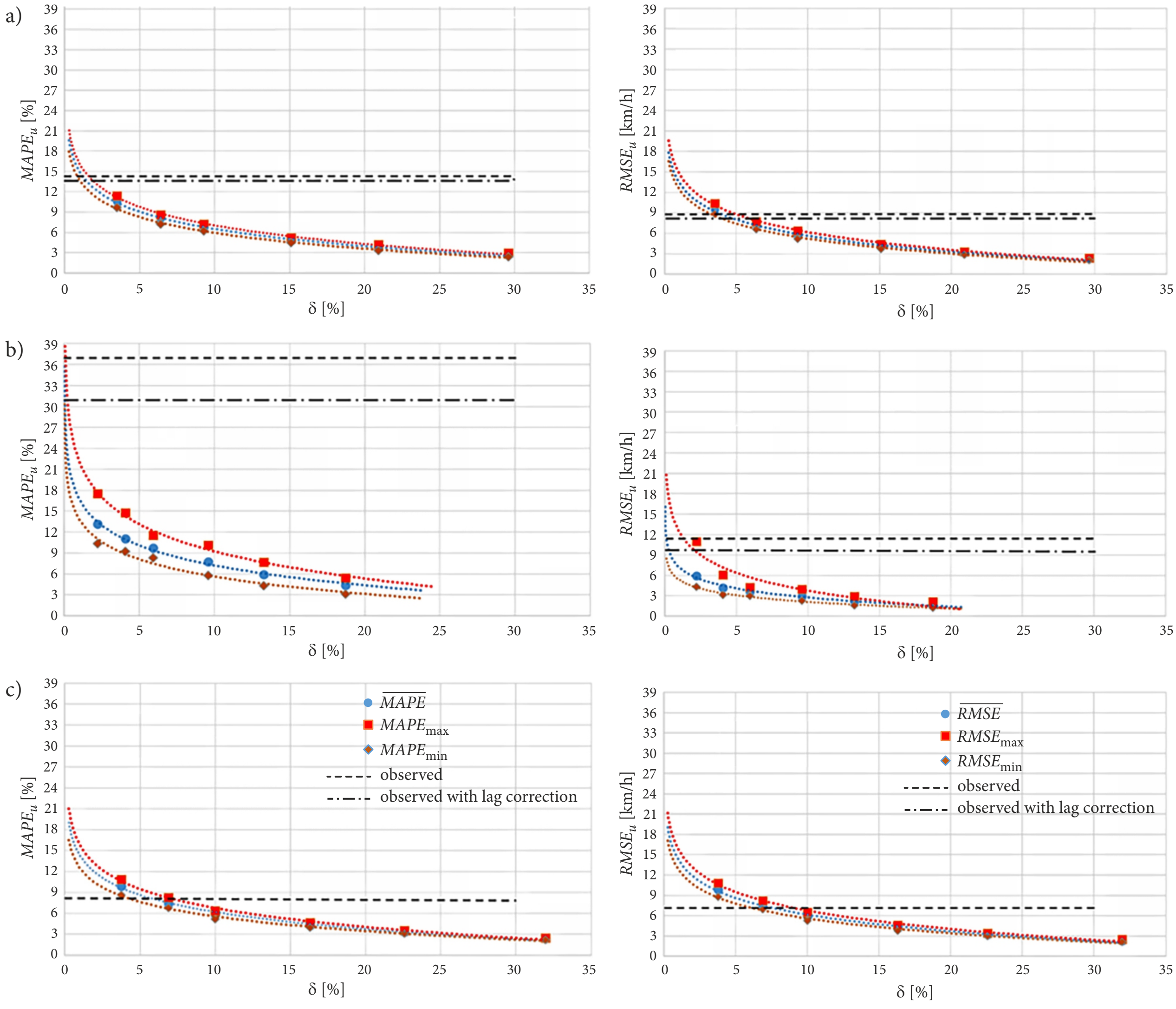

Figure 7. $MAPE_u$ and $RMSE_u$ values from the simulated FCD and commercial FCD sets versus PR for: a – whole-analysis period; b – am-peak period; c – off-peak period

most favourable cases based on MAPE and RMSE relations, respectively.

As discussed above, traffic flow conditions can change significantly between the am-peak period and off-peak period, for which $\hat{\delta}^{FCD}$ estimation was repeated. Using the relations in Equations (UP1a) and (UP2a), traffic PR for the commercial FCD $\hat{\delta}^{FCD}$ was estimated to be as low as 0.2 % based on the MAPE relation. It should be noted here that there was higher variability in the MC scenarios during the am-peak under very low PRs. Thus, the estimated $\hat{\delta}^{FCD}$ values lower than 2.21%, may not be particularly reliable because they were beyond the Q-PR regression data range. In the most favourable conditions $\hat{\delta}^{FCD} = 2.12\%$ was estimated based on the Q-PR function of $RMSE_{u,\max}$ using lag-corrected filtered FCD. During the off-peak period, the commercial FCD traffic PR $\hat{\delta}^{FCD}$ was estimated to be somewhere between 1.62% (from $MAPE_{u,\min}$) and 5.63% (from $MAPE_{u,\max}$), with an average of 4.49%. Q-PR relations for $RMSE_u$ proposed a slightly higher traffic PR of $\hat{\delta}^{FCD} = \{1.72\%, 7.34\%\}$.

Table 4. Simulation-based on Q-PR relations

Q-PR equations based on $MAPE_u$	R^2	Q-PR equations based on $RMSE_u$	R^2
From whole-day speed data (UW)			
$MAPE_{u,\max} = -3.944 \cdot \ln(\delta) + 16.128$ (UW1a)	0.995	$RMSE_{u,\max} = -3.769 \cdot \ln(\delta) + 14.843$ (UW2a)	0.996
$\overline{MAPE}_u = -3.678 \cdot \ln(\delta) + 14.991$ (UW1b)	0.997	$\overline{RMSE}_u = -3.421 \cdot \ln(\delta) + 13.514$ (UW2b)	0.993
$MAPE_{u,\min} = -3.376 \cdot \ln(\delta) + 13.710$ (UW1c)	0.997	$RMSE_{u,\min} = -3.179 \cdot \ln(\delta) + 12.532$ (UW2c)	0.997
From off-peak speed data (UO)			
$MAPE_{u,\max} = -3.921 \cdot \ln(\delta) + 15.808$ (UO1a)	0.996	$RMSE_{u,\max} = -3.958 \cdot \ln(\delta) + 15.887$ (UO2a)	0.994
$\overline{MAPE}_u = -3.528 \cdot \ln(\delta) + 14.329$ (UO1b)	0.989	$\overline{RMSE}_u = -3.550 \cdot \ln(\delta) + 14.334$ (UO2b)	0.993
$MAPE_{u,\min} = -3.019 \cdot ln(\delta) + 12.518$ (UO1c)	0.994	$RMSE_{u,\min} = -3.163 \cdot \ln(\delta) + 12.885$ (UO2c)	0.991
From am-peak speed data (UP)			
$MAPE_{u,\max} = -5.611 \cdot \ln(\delta) + 22.163$ (UP1a)	0.989	$RMSE_{u,\max} = -3.768 \cdot \ln(\delta) + 12.428$ (UP2a)	0.966
$\overline{MAPE}_u = -4.133 \cdot \ln(\delta) + 16.753$ (UP1b)	0.994	$\overline{RMSE}_u = -1.932 \cdot \ln(\delta) + 7.1872$ (UP2b)	0.995
$MAPE_{u,\min} = -3.580 \cdot \ln(\delta) + 13.875$ (UP1c)	0.966	$RMSE_{u,\min} = -1.410 \cdot \ln(\delta) + 5.3434$ (UP2c)	0.990

Table 5. Estimated traffic PR of commercial FCD-based on Q-PR relations

$MAPE_u$					$RMSE_u$				
Observed [%]		Q-PR relation	Estimated FCD $\hat{\delta}^{FCD}$ [%]		Observed [km/h]		Q-PR relation	Estimated FCD $\hat{\delta}^{FCD}$ [%]	
raw	filtered		raw	filtered	raw	filtered		raw	filtered
whole-day (UW)									
17.22 (14.66)	13.65 (12.76)	UW1a	0.76 (1.45)	1.87 (2.35)	11.67 (11.01)	8.73 (8.30)	UW2a	2.32 (2.76)	5.06 (5.67)
		UW1b	0.54 (1.09)	1.44 (1.83)			UW2b	1.71 (2.08)	4.05 (4.59)
		UW1c	0.35 (0.75)	1.02 (1.32)			UW2c	1.31 (1.61)	3.31 (3.79)
am-peak (UP)									
47.52 (32.32)	36.94 (31.29)	UP1a	0.01 (0.16)	0.07 (0.20)	13.87 (10.15)	11.72 (9.60)	UP2a	0.68 (1.83)	1.21 (2.12)
		UP1b	– (0.02)	0.01 (0.03)			UP2b	0.36 (0.63)	0.51 (0.69)
		UP1c	– (–)	– (0.01)			UP2c	– (0.03)	0.02 (0.05)
off-peak (UO)									
11.07	9.03	UO1a	3.35	5.63	11.17	8.01	UO2a	3.29	7.34
		UO1b	2.52	4.49			UO2b	2.44	5.94
		UO1c	1.62	3.17			UO2c	1.72	4.67

Note: "–" represents estimated FCD PR values less than 0.005%.

Among the set of estimated traffic PR values for the commercial FCD at the study location, it is important to select the most reliable one(s) based on not only the derived Q-PR relations but also the real conditions in the traffic as follows:

- there was no evidence/reason for a vehicle type bias in the commercial FCD data among different time periods (i.e., restriction of any vehicle during peak hours, etc.); thus, this is not expected to be a significant factor changing the PR during the peak versus off-peak hours;
- the number of observed vehicles during both off-peak and am-peak periods were almost the same (1 min flows in Figure 3) despite a significant difference in the speed levels; thus, probabilistically, there should be a similar number of vehicles equipped with GPS feeding into the commercial FCD process. However, since the traffic speeds were low, the number of speed observations during the am-peak was smaller (as it took longer to track a vehicle for speed measurements in the video camera-based approach). Consequently, the number of speed observations for the am-scenarios in the MC simulations was low, creating particularly large error levels as well as larger differences between maximum and minimum Q-PR relations. Thus, the reliability of Q-PR relations for the am-peak period may be lower than the reliability of those for the off-peak period;
- since there were more observations during the off-peak hours, the whole-day results are dominated by the off-peak characteristics. Thus, it is recommended to work with off-peak relations instead of whole-day ones. During the off-peak period, high levels of traffic PRs were estimated in the range of 3.17…5.63% (by MAPE) and 4.67…7.34% (by RMSE).

Consequently, using the estimated traffic PR from the off-peak period Q-PR relations, we can conclude that the current traffic PR of FCD is 3…7% at the study location. This result is higher than the reported market FCD PR of 3% by vehicle registration numbers, which may be reasonable, as latter may be lower due to consideration of total number of registered vehicles in Turkey, which may not be always traveling on the urban roads. However, it should be noted that (1) the proposed Q-PR relations show the change of error levels in MAPE or RMSE due to only PR difference, as they are created in simulated environment with no other contributing error sources (such as time-lagging, missing data for certain time periods in case of congestion or very low volumes, etc.); (2) even though commercial FCD values were improved by eliminating the outliers and observed 4 min lag roughly, there may still be other sources of errors in the commercial FCD data (such as the use of historical values in combination with real-time data), which may increase the observed errors; in return, resulting in lower $\hat{\delta}^{FCD}$ estimations. Thus, in the estimation of the traffic PR of FCD using derived Q-PR relations based on a GT data set, it is recommended to use the average off-peak estimations $\hat{\delta}^{FCD} = \{4.49\ldots5.94\}$ (approximately 5% traffic PR) for the study location.

Conclusions

The increasing availability of GPS-equipped vehicles in traffic will ensure that FCD remains a promising traffic data source, particularly for urban arterial management due to its low cost and high coverage capability. Although individual tracking data from GPS-equipped vehicles convey highly detailed and reliable information on traffic state (e.g., space–time diagram and queue entrance–exit locations), it is not feasible for local authorities to collect and process such detailed big data; thus, they seek commercial FCD, which are processed regionally and published continuously (even at 1 min time intervals for segments as short as 50 m in length). However, this commercial processing also brings concerns regarding the size of sampling for each data interval, the PR, as well as the randomness of the sampling, which requires quality evaluation.

The proposed methodology included, first, monitoring of the MoEs (MAPE and RMSE) for varying PRs simulated from a GT speed dataset, creating a set of Q-PR relations. The same GT dataset was, then, used to evaluate the same measures for the commercial FCD speeds at the same location. Comparisons of the MoEs and Q-PR relations finally led to estimation of the traffic PR for the commercial FCD, which was the main objective of this study. The results showed that there was a logarithmic decrease in the MAPE and RMSE values as the PR in the FCD increased, as expected. The derived Q-PR relations had very high R^2 values, even for lower PRs and congested conditions. FCD PRs of 15%, produced very reliable FCD speed values, which was also suggested as a critical level in traffic flow estimation for connected vehicle technology (Talebpour, Mahmassani 2016). Estimated traffic PRs for the study location was found around 5%. This seems to be a promising capacity for FCD to be used as an urban traffic data source for a developing country.

It is necessary to evaluate the quality and the actual PR at selected locations (on major corridors, etc.) and time intervals (annually or so) using a GT data source, even sampled. It should be noted that the model performance for estimating the PR of the commercial FCD should be tested for multiple locations, different FCD segment lengths and different road types (such as signalized arterials), which will be the focus of further studies. Thus, before providing a conclusion about the traffic PR of a commercial FCD in an urban region, possible GT data collection locations must be selected based on a pre-assessment of traffic volumes and conditions on urban arterials. Increase in the FCD PR in the future will surely increase the reliability, especially if it includes more GPS data collected from vehicles of individual users (private cars, taxis) as opposed to slow fleets (bus, trucks, etc.) and smaller sampling intervals (i.e., 30 sec). If vehicles tracked by the commercial FCD companies used the network randomly, $\hat{\delta}^{FCD}$ during peak hours would not differ much from the off-peak values, but, observation of these vehicles at every min would be more challenging, thus create larger errors in the commercial FCD during congested flow regimes. This may be the reason behind the very low $\hat{\delta}^{FCD}$ in the am-peaks in this study.

The higher the market PR in a region, the more likely it is to have a higher traffic PR, which can also be estimated with high reliability. However, the latter is subject to have spatio-temporal variations by nature in very short-terms; but, considering the repeating nature of commuting travel demand and even slower rate of change in vehicle ownerships in urban regions, traffic PR estimated for a location is expected to be representative for longer terms (1…2 years).

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Author contributions

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Data collection and analysis were especially performed by *Oruc Altintasi* and *Hediye Tuydes-Yaman*.

All authors were responsible of the data interpretation.

Oruc Altintasi wrote the draft of the article, and whole part of the manuscript has been carefully prepared and read by the all authors.

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