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Evaluation of trade-offs between two data sources for the accurate estimation of origin-destination matrices

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Evaluation of trade-offs between two data sources for the accurate estimation of origin–destination matrices

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In this paper, we evaluate the trade-offs between loop detector data and floating car data (FCD) for the real-time estimation of origin–destination (OD) matrices in small networks. The proposed methodology is based on a bi-level optimisation using fuzzy logic theory. Here we demonstrate that it provides accurate results with low computational cost, while presenting several advantages over other existing algorithms (especially in terms of data requirements, computational complexity, and quality of adjustment). The methodology is illustrated with three examples covering two different locations in the city of Zurich, Switzerland. Results are used to evaluate the trade-offs between loop detector coverage and the penetration rate of FCD, and to determine minimum values for ensuring a given accuracy level on the estimated OD matrices. In general, the resulting error in OD estimation is affected by the data redundancy in the network.

Keywords: origin–destination (OD) matrix estimation; floating car data; loop detectors; bi-level optimisation; fuzzy logic

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1. Introduction

The knowledge of traffic flows between defined origins and destinations in a road network represents the predominant form of information required by planners and engineers for effective traffic management and control. Origin–destination (OD) matrices are of vital importance for transportation systems planning and design, as well as analysis, modelling, and simulation. They contain information about the spatial and temporal distribution of activities (and the resulting traffic) between different points (or zones) in an urban area (i.e. each cell represents the number of trips between an origin and a destination). OD matrices are used to represent the current demand for transportation systems; or, based on anticipated economic and population growth, land-use changes, and planning policies, to identify and forecast the future demand and other alternative scenarios.

In order to get an accurate OD estimation, several types of data are now being used in addition to the traditional link flow counters; including multisensor data (Biletska et al. 2009) and floating car data (FCD). The latter are an essential source for traffic information and for most intelligent transportation systems (ITS). FCD are obtained from appropriately equipped vehicles that act as moving sensors for the road network. Based on FCD, traffic flows can be identified, travel times

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can be calculated, and traffic reports can be instantly generated. There are two main types of FCD in operation today: cellular FCD data, derived from cellular networks, and global positioning system (GPS)-based FCD, derived from different type of devices that are equipped with a GPS receiver.

Since FCD are becoming increasingly common, in this paper, we focus on evaluating the trade-offs between different combinations of loop detector data and FCD, for estimating OD matrices in small networks. This data combination is rather promising and could be highly valuable in identifying not only demand patterns but other more operational traffic aspects (Heimgartner and Menendez 2013). We also determine the expected accuracy for different levels of FCD penetration rates (FCD-PR) and loop detector coverage (LDC); and illustrate the minimum requirements for a given accuracy threshold. The proposed methodology is based on a bi-level optimisation (BO) using fuzzy logic theory, and presents several advantages over other existing algorithms for OD estimation: (i) it does not require historical OD information for a seed matrix, a priori information about proportions of movements or the most likely OD paths, or route specific probabilities for FCD. (ii) It involves a linear optimisation process, so computational costs are lower than for other non-linear methods. (iii) It provides better adjustment than other fuzzy optimisation methods, such as the maximisation of the minimum membership grade or the maximisation of the sum of membership grades, as well as the classic least-squares method (see de Oña, Gómez, and Mérida-Casermeiro 2011, 2014, for more details on this last advantage).

The proposed methodology is illustrated with three examples covering two different locations. The first location includes a simple intersection, and it is used for reference purposes. The second location is a more complex network encompassing three intersections, and it is used to test the transferability of the method and its flexibility with more complex situations. Data for both locations are obtained from a VISSIM micro-simulation model of the inner city of Zurich, Switzerland, that has been calibrated on flows.

Overall, the two main contributions of this paper are:

- the introduction of a new BO method for the estimation of OD matrices that has clear advantages over other existing methods (see above);
- the evaluation of trade-offs between FCD-PR and LDC for different accuracy levels on the estimation of OD matrices.

The rest of this paper is organised as follows: In Section 2, we present a brief literature review on OD matrix estimation and the use of FCD. In Section 3, we introduce the methodology and the required inputs. In Section 4, we apply the new method to the two locations in Zurich, and discuss the results. In Section 5, we highlight the findings from the paper and present some final remarks.

2. Literature review

2.1. *Intersection OD matrices*

OD matrices are an essential input to traffic assignment models, which in turn are often used in simulations of transportation systems. They are typically estimated based on surveys and adjusted with infrastructure-based sensors capable of measuring vehicle flows (e.g. loop detectors), sometimes combined with other data sources. Regardless of the method used, the purpose is to obtain an OD matrix that yields link flows as close as possible to those observed in reality.

The previous research works on OD matrix estimation at a junction are based on methods of minimisation principle (Van Zuylen 1979), maximisation of likelihood (Hauer, Pagitsas, and Shin 1981), or Bayesian inference (Maher 1983). Other methods present the estimation as a constraint

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optimisation problem (Sherali, Arora, and Hobeika 1997; Li and De Moor 1999; Tarko and Lyles 2001). However, all the former methods generally yield estimates of the OD flow over a long time period, and can only be applied to simple two-road-crossing junctions. Moreover, none of the cited methods considers the redundancy, uncertainty, and imprecision of the data. A short-time estimation of OD matrices at a signallised junction with complex structure was proposed by Biletska et al. (2009) using information from video cameras. They defined a methodology based on the conservation law of vehicles at each traffic light cycle.

Other authors (Guozhen et al. 2011) have proposed using the combination of link flow measures and automatic vehicle location information to estimate dynamic ODs by applying a generalised least-squares model. Such a model considers, however, 100% link measurements availability. This paper presents a method that has been proven to be better than the least-squares method and other fuzzy optimisation processes (de Oña, Gómez, and Mérida-Casermeiro 2011, 2014). Moreover, it is used even in the absence of perfect information (i.e. estimates are made for less than 100% link measurements availability).

2.2. *Network OD matrices*

Existing methods typically start from an a priori estimate (i.e. seed matrix) that is adjusted according to some algorithm. Evidently, the quality of the seed matrix is a determinant factor on the accuracy of the results. The adjustment process, however, changes with the type of algorithm employed, and can improve with the use of additional information. Estimating OD matrices only from loop detector counts can be rather challenging given the indeterminate relation between observations and route flows (Parry and Hazelton 2012). Loop detectors provide information on the number of vehicles that cross them, but not on the trajectory these vehicles take. To forecast an OD matrix from loop detector information, a seed matrix with, e.g., a proportion of movements is needed. Hence, many researchers have tried to integrate other additional traffic metrics. Examples include roadside surveys; speed and density data (Balakrishna 2006; Cipriani et al. 2011); manual plate registration (Watling 1994); other automatic vehicle identification technology (Sun and Feng 2011); and FCD (Antoniou, Ben-Akiva, and Koutsopoulos 2004; Zhou and Mahmassani 2006; Guozhen et al. 2011; Barceló et al. 2012; Parry and Hazelton 2012; Vandenberghe et al. 2012). The literature review regarding FCD requirements does not provide yet, however, accurate indications to support the feasibility of FCD in the context of traffic-collected data. This paper presents the evaluation of trade-offs between FCD-PR and LDC in order to estimate an OD matrix applying a BO fuzzy method (de Oña, Gómez, and Mérida-Casermeiro 2011, 2012, 2014) where linear programming is used. The inherent imprecision of data is modelled by triangular fuzzy numbers. The historical knowledge about the values is not used in order to ensure that all data used are real-time and to avoid the uncertainty of historical data. The proposed method, contrary to most established OD estimation algorithms, does not require a seed matrix. Even though it would be easy to incorporate the historical data as an input, we have omitted this information in order to better demonstrate the proposed methodology. Moreover, the method is fed by a portion of the counters measurement (i.e. not necessarily 100%) plus different amounts of FCD. The FCD are used to identify sporadic vehicle routes.

2.3. *Location of traffic sensors*

So far, to estimate an OD demand with precision it was necessary to determine the proper number and location of traffic sensors, as its quality was related to the amount of flow measurements the analyst was able to make. Choosing the proper location is known as the network sensor location problem (NSLP) (Bianco, Cofessore, and Reverberi 2001; Hu, Peeta, and Chu 2009). Within this field, some authors have proposed different domains related to the network observability problem

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(Castillo et al. 2007), where the state of traffic flow can be partially or fully presumed from the observation of partial link flow measurements (Gentili and Mirchandani 2012). Three approaches are known to solve the NSLP problem. The first approach maximises flow coverings using a mathematical optimisation approach (Yang and Zhou 1998; Yim and Lam 1998; Teodorovic et al. 2002; Ehlert, Bell, and Grosso 2006; Hu and Liou 2012), or searches for the minimisation of some requirements where different constraints ensure the flow conservation (Chen, Chootinan, and Pravinvongvuth 2004; Mínguez et al. 2010). The second approach uses matrix algebra through one-step or iteration procedures. Some authors have developed the matrix algebra based on the link–path incidence (Castillo et al. 2007, 2008a, 2008b, 2013; Castillo, Menendez, and Jimenez 2008; Castillo, Menendez, and Sanchez-Cambronero 2008; Hu, Peeta, and Chu 2009), while others have used the link–node incidence matrices (Ng 2012); in both cases to outline a set of deployed links. The third approach considers the spatial relationships between links and nodes in a network structure, and uses graph theory to find the critical links (Bianco, Cofessore, and Reverberi 2001; Gentili and Mirchandani 2005; He 2013).

Recently, Ortigosa, Menendez, and Tapia (2014) tested different strategies for obtaining accurate flow and density values over an urban network. They did not consider, however, the impact of the strategies on the development of OD matrices. Hu and Liou (2014) developed a strategy to choose the best situation for different sorts of traffic sensors in order to obtain a proper OD estimation. Their model succeeds in solving both the sensor flow-observability problem (i.e. link flow inference) and the sensor flow-estimation problem (i.e. network O–D demand estimation) under budget constraints. The novelty of the latter is that no prior demand information is required such as route choice probabilities or turning proportions.

2.4. *FCD*

The possibility of collecting longitudinal data has been available since the late 1990s, e.g. with in-vehicle GPS devices combined with geographic information systems. Nowadays, FCD can also be obtained with mobile phones, electronic toll collection devices, and bluetooth devices, among others.

Sometimes, FCD are collected in combination with other more traditional methods (e.g. travel diary studies). The goal is typically to capture and evaluate the errors associated with the other more general types of data, e.g. to record exact trip times and destinations and capture trip underreporting in travel diaries (Wolf, Oliveira, and Thompson. 2003; Ogle et al. 2005). These efforts often involve driver–computer interaction, and at the very least driver–survey interaction. In other cases, FCD are collected in a passive manner (i.e. without any information input by the drivers; Lee-Gosselin 2002). These efforts are typically driven by specific concerns (such as traffic safety), and often require extensive data post-processing (see Wolf et al. 2004 and Ogle 2005, for relevant examples). In this paper, we will use passive FCD. Moreover, the position of the vehicle will only be used to extract its routing. For this, it is possible to use information transmitted by on-board WiFi devices or GPS devices. Since the range of the WiFi signal is typically rather small and many roadside units would be needed to properly capture data at a network level, we will focus more on GPS devices. Notice, however, that as long as the information exists, for the purpose of the methodology proposed here, the type of device that provides that information is not important.

For GPS devices the positioning accuracy under ideal conditions lies between 5 and 10 m (Wolf 2006). In reality, however, it is usually worse due to several error sources. For instance, the GPS navigation device might not have at some points direct access to the four satellites required to precisely calculate a three-dimensional position (Wolf et al. 1999); or data might be missing from the beginning of trips due to the time the GPS device needs for acquiring the position of

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at least four satellites (Stopher, Jiang, and FitzGerald 2005). In addition, there might be random errors caused, for example, by satellite or GPS device issues, atmospheric and ionospheric disturbances, multi-path signal reflection, or signal blocking (Jun, Guensler, and Ogle 2007). Especially troublesome are multi-path errors, where the GPS signal is reflected by buildings, walls, or surfaces; and the corresponding GPS positions jump and are often scattered around the actual position of the GPS navigation device (Schuessler and Axhausen 2008). Notice, however, that standards for GPS in 2009 required for civil applications in the USA an accuracy within 9 m horizontally and 15 m vertically 95% of the time (DOT USA 2006). That level of accuracy is enough for our purposes (i.e. to track vehicles routing almost perfectly at network levels, even in small networks).

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3. Required inputs and methodology

In this section we introduce the BO method using fuzzy logic for the estimation of OD matrices. We first introduce the proposed methodology followed by the data to be used, and the inputs required.

3.1. *Methodology*

As previously mentioned, the proposed methodology uses a BO method that employs fuzzy logic theory. As it has been shown in de Oña, Gómez, and Mérida-Casermeiro (2011), this method provides better adjustment of the field data than other fuzzy optimisation methods, such as the maximisation of the minimum membership grade or the maximisation of the sum of membership grades (more details are given below). In previous works, the method has been applied for obtaining a consistent set of adjusted values from the observed inconsistent values collected in road networks (de Oña, Gómez, and Mérida-Casermeiro 2011); for detecting malfunctioning detectors with no need for historical data (de Oña, Gómez, and Mérida-Casermeiro 2012); and for adjusting boarding and alighting passengers in a transit line (de Oña, Gómez, and Mérida-Casermeiro 2014). In this paper we will use the method for the first time to evaluate the data trade-offs for the estimation of OD matrices in a network. Notice that in de Oña, Gómez, and Mérida-Casermeiro (2014) it was demonstrated that this method provides better adjustment than the classic least-square method (LSM), which is often used to estimate static and dynamic OD flows (Doblas and Benitez 2005; Guozhen et al. 2011).

Other methods used in this field require historical OD information for a seed matrix as in, for example, Antoniou, Ben-Akiva, and Koutsopoulos (2004), Zhou and Mahmassani (2006); a priori information (e.g. most likely OD paths) as in, for example, Barceló et al. (2012); or route specific probabilities for FCD (i.e. the probability that a vehicle is tracked on each individual route) as in, for example, Parry and Hazelton (2012). Here, we estimate (a priori) the FCD-PR directly from the loop detector data (e.g. if FCD are obtained only from 3 vehicles crossing a loop detector that counts 30 vehicles, FCD-PR is estimated as 10%). The resulting values are then entered directly into the methodology to estimate the total number of vehicles based on the number of vehicles providing FCD. Another possibility would be to enter the FCD-PR as a variable into the problem. Although feasible, this would convert the problem into a non-linear programme and the computational costs would increase.

Once the FCD-PR is estimated, the first step is to define membership functions to represent the available information from loop detectors and FCD. This allows us to take into account the inherent uncertainty of the data. Figure 1 shows the shape of the membership function with the centre value x_i^{obs} and a range $[x_i^{obs} - \alpha_i \cdot x_i^{obs}, x_i^{obs} + \alpha_i \cdot x_i^{obs}]$, where α_i is a constant higher than 0. The adjusted value x_i will be found within this membership function.

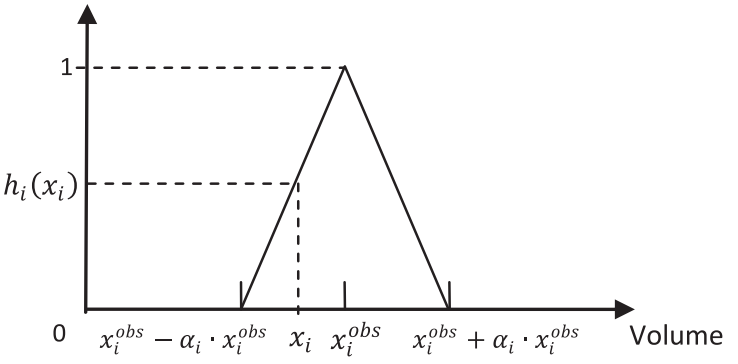

Figure 1. Membership function.

A membership function is convenient for representing the idea that the adjusted value should be close to the observed value. Hence, the acceptability of the adjusted value gradually diminishes as it deviates from the observed value. A large volume of literature is available on interpretations and applications of fuzzy sets and membership functions. See Tanaka (1990), Yager and Filev (1994), Zimmermann (1996), and Klir and Wierman (1999) for more details.

Here, based on the literature on full fuzzy linear programming using symmetric triangular fuzzy numbers (Lotfi et al. 2009), we assume triangular-shaped membership functions. This representation is computationally convenient as a linear programme can then be used. Thus, this can be solved with any of the software available as it is reduced to a mixed linear programming formulation since we have integer numbers (vehicles) and real numbers (membership grades). Notice that if we have different measurement devices (i.e. permanent or sporadic), different tolerances (usually expressed as a percentage of the observed value) are expected. For instance, if sensor A is expected to have errors up to $\pm 3\%$ and sensor B up to $\pm 7\%$, α_i would be 0.03 and 0.07 for the observed values in sensors A and B, respectively. Then, x_A would be found within the interval $[x_A^{obs} - 0.03 \cdot x_A^{obs},\ x_A^{obs} + 0.03 \cdot x_A^{obs}]$ and x_B within $[x_B^{obs} - 0.07 \cdot x_B^{obs},\ x_B^{obs} + 0.07 \cdot x_B^{obs}]$. Equation (1) defines the membership function. Notice that if additional information about the character of the observed value is available, the shape of the membership function could be modified (e.g. its triangular shape or the size of the base) and the solution would not change.

$$h_i(x_i) = \max\left\{0, 1 - \frac{|x_i - x_i^{obs}|}{\alpha_i \cdot x_i}\right\}, \tag{1}$$

where x_i is the adjusted value for the ith variable. That is

$$\forall i; \quad x_i \in [x_i^{obs} - \alpha_i \cdot x_i^{obs}, x_i^{obs} + \alpha_i \cdot x_i^{obs}].$$

The selection of the constant α_i depends on the judgement of the analyst with respect to the adjusted value's acceptable deviation from the observed value. In a complex transport network, there may be permanent traffic count stations where count data are fairly reliable, and other nodes where counting is sporadic, as well as points where traffic volumes have not been measured. The values of α_i will depend on whether the parameter belongs to either of those data sets (i.e. more reliable data will have a lower value of α_i); for details see de Oña, Gómez, and Mérida-Casermeiro (2011). If only one value of α_i is used for all data, then the defined range has little effect on the final adjusted values, assuming that it is broad enough for a feasible set of solutions to be found.

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In the case analysed, there are two types of collected data (FCD and loop detector data). Therefore, to define the α_i parameter coherently, we assign different values to it, based on the reliability of the data sources. It seems obvious that loop detector data can be considered more accurate than FCD (given the unknown FCD-PR and the other uncertainties explained in Section 2). Hence, a smaller $\alpha_i = 1.5\%$ is assigned to the loop detector data (so that loop detector adjusted data will be within a deviation of $\pm 1.5\%$ from the observed data) than to the FCD ($\alpha_i = 30\%$). Notice that if the loop detectors were likely to be failing, then a bigger α_i could be taken. In any case, recall that the size of α_i does not influence the adjusted value, only the membership grade (which is not taken into account in the results). In other words, the value of α_i is only a condition used within the optimisation process (see de Oña, Gómez, and Mérida-Casermeiro 2012 for more details). For instance, let A and B be two sets of α_i, such as $A = \{\alpha_1, \alpha_2, \ldots, \alpha_n\}$ and $B = \{k \cdot \alpha_1, k \cdot \alpha_2, \ldots, k \cdot \alpha_n\}$, where $k > 0$. If $h_i^A > 0$ and $h_i^B > 0$ are the h_i obtained by applying Equation (1) with the sets A and B, in both cases the vector X (set of x_i) obtained after applying the bi-level method is the same.

Given then a set of observed values $\{x_i^{\text{obs}}\}$, $i \in I_{\text{mov}} \cup I_{\text{loop}} = I$ (where I is a set of indexes, and I_{mov} and I_{loop} are the number of movements (flow paths from origins to a destinations) and loop detectors, respectively) each with a tolerance of α_i ($\pm 30\%$ for the movements because this information is collected from the FCD, and $\pm 1.5\%$ for the loop detectors), we define the feasible region as the set $A \subset R^n$, such that $\forall \vec{x} = \{x_i\} \in A$, where the following conditions are satisfied:

- Condition 1: $x_i^{\text{obs}} - \alpha_i \cdot x_i^{\text{obs}} \leq x_i \leq x_i^{\text{obs}} + \alpha_i \cdot x_i^{\text{obs}}$, where x_i^{obs} is the number of vehicles observed that have made the movement $i \in I_{\text{mov}}$, or that have been counted by the loop detector $i \in I_{\text{loop}}$; and x_i is the adjusted value based on the observed value.
- Condition 2: Vector $\vec{x}$, must satisfy the flow conservation law $\sum_{i \in I_{\text{loop},\,j}} x_i = \sum_{i \in (I_{\text{loop}} - I_{\text{loop},\,j})} x_i$, where $I_{\text{loop},\,j} \in I_{\text{loop}}$ is the set containing loop detectors on the lanes entering the intersection; and $I_{\text{loop}} - I_{\text{loop},j} \in I_{\text{loop}}$ is the set containing loop detectors on the lanes exiting the intersection.

Assuming $x_i^{\text{obs}} \geq 0$, $\forall i \in I$, it is now possible to get the adjusted value by finding out the best solution to the linear optimisation problem proposed. The methodology comprises two levels and was already introduced by the authors in de Oña, Gómez, and Mérida-Casermeiro (2011):

Level 1: The problem is solved using the MaxMin method (MM method) (Equation (2)), and we obtain a value of $h = \min(h_i)$

$$\max(\min(h_i)). \tag{2}$$

Subject to

- Constraints related to the membership functions:

$$h_i(x_i) \geq h \quad \text{for } i = 1, 2, \ldots, I. \tag{3}$$

- Constraints related to the conservation of flow in the network:

$$\sum_{i \in I_{\text{loop},j}} x_i = \sum_{i \in (I_{\text{loop}} - I_{\text{loop},j})} x_i, \quad \forall j. \tag{4}$$

- Constraints related to the relationships between the loop detectors and the movements. For the specific case shown in Figure 2, these relationships are shown in Tables 1 and 2.

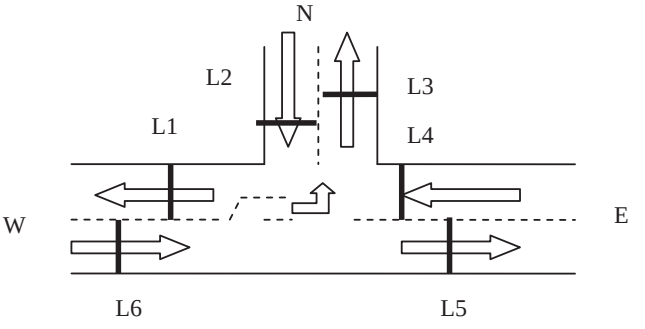

Figure 2. Illustrative example of loop detectors and movements in intersection.

Table 1. OD movements.

O/D	E	N	W
E	–	x_1	x_2
N		–	x_3
W	x_4	x_5	–

Table 2. Relationships between loop detectors and movements.

O/D	E	N	W
E	–	Loop 4, Loop 3	Loop 4, Loop 1
N	–	–	Loop 2, Loop 1
W	Loop 6, Loop 5	Loop 6, Loop 3	–

Obviously, these relationships are closely related to the network, so they have to be adapted to each situation. To clarify, let us use as an example the movement from North to West (row 2, column 3), corresponding to movement x_3 in Table 1. Loop detectors 2 and 1 (Figure 2) will count the vehicles that make this movement. In other words, loop detector 1 (placed in the exit to the West) will be related to all the movements going to the West (coming from any direction). That means that it will appear in every row for column 3 (as long as the movement exists). These relationships can be translated into a linear equation system (this conversion into the linear equation system can be easily obtained automatically from the matrix in Table 2), in this case:

$$\text{Loop } 1 = x_2 + x_3, \quad \text{Loop } 4 = x_1 + x_2, \tag{5}$$

$$\text{Loop } 2 = x_3, \quad \text{Loop } 5 = x_4, \tag{6}$$

$$\text{Loop } 3 = x_1 + x_5, \quad \text{Loop6} = x_4 + x_5. \tag{7}$$

Due to this condition there will be as many constraints as number of loop detectors. So, in total, there will be $|I_{\text{loop}}| + 1$ equality constraints (including the one from Equation (4)).

Once level 1 is finished, the optimum value for $h = h^*$ is recorded.

Level 2: The problem is solved using the Max Sum method (Equation (6)).

$$\max(\text{sum}(h_i)). \tag{8}$$

Subject to the same constraints for the conservation of flow and the relationships between detectors and movements (Equations (4) and (5)), as well as to the following constraints related

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to the membership functions:

$$h_i(x_i) \geq h^* \quad \text{for } i = 1, 2, \ldots, n, \tag{9}$$

where n is the cardinal of I. The total number of unknowns in Step 2 is reduced by one compared to Step 1, because the maximum minimum h_i in this step is known and equal to h^*.

If only MM is performed (level 1), there may be several imputations for the observed data that produce the same value for h (Tussel 2002; Silva-Ramírez 2007). Therefore, they would be the same from the objective function point of view, whereas, in fact, some are better than others. The combination (0.9, 0.9, 0.9), for instance, would yield the same value as (0.9, 1, 1), whereas the latter is better than the former. On the other hand, if the objective function were just MaxSum (level 2), some values would show an $h_i = 0.00$, despite the fact that almost all the rest are 1.00, which is of no interest. The BO process here proposed allows the combination where the remaining membership degrees are the highest ones to be chosen from among all the combinations where the lowest value of h is maximised.

This method is an nondeterministic polynomial time-hard problem, where the first step is a linear programming problem to obtain real solutions, and the second step is a routine to obtain the solution within the feasible region (which could be a quasi-optimum that allows the problem to be solved in a reasonable time).

This is important, because for tackling a problem in real-time we need a computationally efficient method. Notice that the membership functions allow us to keep the problem linear, even if it is an integer problem. Once the adjustment is made by the double optimisation process, the absolute average error is obtained in order to verify the results (Guozhen et al. 2011). We define the mean of the relative error in the form of a percentage as

$$\varepsilon = \frac{100}{n} \sum_{i=0}^{n} \frac{|x_i - x_i^{\text{true}}|}{x_i^{\text{true}}}, \tag{10}$$

where x_i is the adjusted value for the ith observed value, x_i^{true} is the true and consistent value, and n is the total number of variables.

By transforming the problem into a linear programming problem, we now can use multiple optimised routines (see de Oña, Gómez, and Mérida-Casermeiro 2011, for more details). When eliminating inconsistencies of observed traffic counts, results reported by Sivanandan, Narayanan, and Lei (1996) and Biletska et al. (2009) revealed that the linear programming approach that we will use is superior to the LINKOD (Gur et al. 1980), and the maximum entropy methodologies (Van Zuylen and Willumsen 1980) in terms of accuracy as well as computational efficiency. The computational costs do not only depend on the amount of data, but fundamentally on the number of parameters in the estimation (number of loops plus number of routes), which evidently introduces complexity. The number of variables, $2 \cdot (|I_{\text{loop}}| + |I_{\text{move}}|) + 1$, includes not only the individual variable for each loop detector and movement, but also the h_i associated with them, plus the $h = \min(h_i)$. Nevertheless, given that the problem can be solved with a linear programme, computational cost is not a concern. For example, in the complete case of the first example described in the next section, with all the data available (i.e. the true and consistent values – something that will not happen in real life), there are 37 variables (from 10 loop detectors and 8 movements). The data include 3249 vehicle counts from detectors (most vehicles are tracked by two loop detectors in this case), and 1626 vehicles tracked with FCD. Using MATLAB in a PC with a 3.16 GHz Intel(R) Core™2 duo CPU processor, this problem can be solved in 0.8 s.

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3.2. *Data*

Data used in this paper are based on a traffic micro-simulation model of the central area of Zurich (around 2.6 km^2) implemented in VISSIM. In this model, several transportation modes are included; however, for our purposes, we only consider cars. The model emulates the signal prioritisation scheme for public transport that the city has implemented. The signal prioritisation scheme affects cars based on the arrival of buses and trams. It also means that traffic lights do not follow a fixed timing control; they are actuated by public transport (so cycles might be different across 1 h). Data used here represent the 5–6 pm afternoon peak demand on a working day. This model has been calibrated using flows from vehicle counts (Heimgartner 2012; Menendez and Ge 2012).

Here we use data from loop detectors and FCD. The former is used to have knowledge of the total vehicles in the network (i.e. counts), and the latter to estimate the OD movements with no need for historical data (i.e. trajectories). In real life, there are different types of FCD and information is not always available at the origin and the destination. Nevertheless, any FCD that provides information about trajectories could be useful in this kind of situations. The VISSIM model used here can provide, depending on its resolution, the position of every vehicle with very high precision (frequency of 10 Hz). However, to match reality better, we have extracted vehicle data (position) at 1 s intervals (i.e. with a frequency of 1 Hz) to follow each vehicle passing through the intersections of interest. Notice that this is a conservative estimate, as low cost GPS devices can transmit with a frequency between 1 and 5 Hz (Leung et al. 2006). Moreover, the vehicle safety communications consortium suggests a broadcast frequency of 10 messages per second (Hartenstein and Laberteaux 2008).

Also, to emulate reality, we have manually placed in the VISSIM network loop detectors on each lane directly upstream and downstream of the intersections of interest. They provide traffic counts aggregated over 5-min periods.

The simulation was run for a period of 60 min, after a warm-up period of 15 min. Here we use the total number of cars that enter and exit the network during that whole hour.

Figure 3 shows a map of the Zurich model, and identifies the two locations used in this study. More details about the two locations are provided in Section 4.

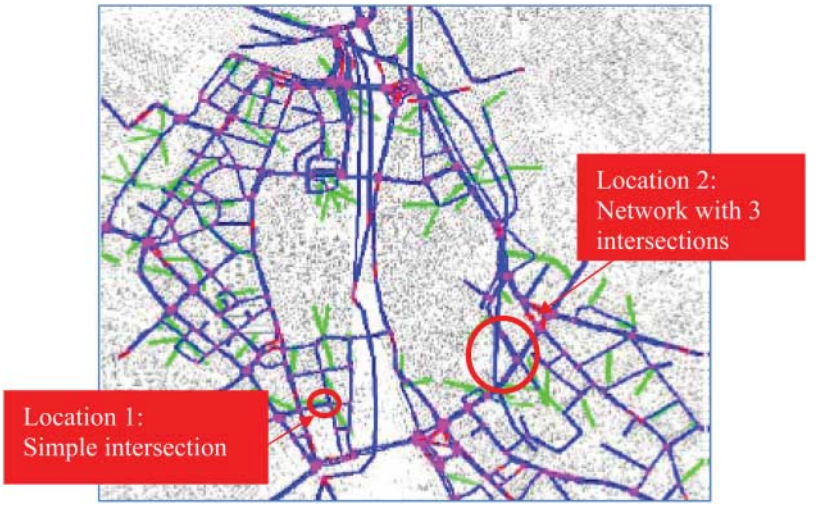

Figure 3. Urban layout.

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As it is exposed above, from VISSIM, all vehicle paths that cross the intersection are available. However, for the different tests we will run on Section 4, we often consider that we only have FCD information from a portion of the vehicles (i.e. less than 100% – a more realistic assumption). The selected level of FCD-PR represents the percentage of vehicles from which we know the trajectory, as we try to emulate the real conditions and our ability to collect information from GPS and other positioning devices. In other words, we still collect the full data set from VISSIM, but only use information from randomly selected vehicles corresponding to different levels of FCD-PR (ranging between 5% and 100%). It is important to emphasise that in our simulation model the FCD has no errors, i.e. we consider this information as exact, and to create different scenarios emulating reality we artificially lose a percentage of this information. Hence, in the case where we assume to have 100% FCD-PR, we basically receive information from all vehicles in the system, so the expected error of our estimations would be 0%. Notice that nowadays, FCD might be related to special fleets such as taxis, or specific car manufacturers (e.g. BMW, Audi, Renault), each providing a separate routing and hence tracking service. Nevertheless, in the VISSIM simulations used here, we assume no bias on the data sources. The objective is to determine the required FCD-PR overall to reach an admissible OD matrix based on different levels of LDC. Since the true and consistent data are also available, the goodness of the method can be verified (absolute relative error). In the case where different types of vehicles would provide different levels of FCD, the methodology presented here could be used multiple times, each to account for each type of data source.

Notice, too, that these examples emulate movements within a small area of a city. Nevertheless, when studying the OD matrices for the whole city, the latter could be split into big representative areas, corresponding, for example, to the cardinal points or different districts. If the area is small enough, within the interval of time considered every vehicle may be able to complete its trajectory. On the contrary, if the area is big, only the vehicles that have finished their movement would be considered. In other words, if we have 15 min time intervals, and from the simulation model we get 30% of the trajectories, then we would expect that only the 25% of those would finish the movement in a given time interval. Thus, after pre-processing the data, only the vehicles that have finished their movement would be selected as an input.

Once the loop detector data plus the FCD are collected, we have the x_i^{true} and we can create sets of inconsistent data (i.e. data that do not satisfy the law of flow conservation, so the total incoming volumes are not equal to the total outgoing volumes at the intersection) by randomly distorting data within $\pm 30\%$. Such sets would represent real data sets, where we might be missing information due to some lanes not having loop detectors, and/or lower than 100% FCD-PR. Our methodology then looks for the 'best' set of adjusted values, close to the ones from the inconsistent set, but satisfying the flow conservation principle.

Previous research works (Argote et al. 2011) have evaluated the minimum FCD-PR needed to obtain accurate estimates for a variety of measures of effectiveness. They established that to guarantee effectiveness, the absolute relative error of the estimation should not exceed 10%. Based on that assumption, they calculated that a 50% FCD-PR was required for the estimation of average speed and average number of stops, 80% for average delay, and 10% for acceleration noise. Here, we will analyse results with the same aim of keeping the average error in the estimation of the OD matrix below 10%.

4. Examples and analysis of results

In this section, the proposed method is illustrated with three examples. The first corresponds to Location 1 and the other two correspond to Location 2 in Figure 3. To validate the method for

different data availability levels and to generalise the results, each example covers different scenarios. The goal is to emulate: (i) different FCD-PR, where this information is used to create a seed OD matrix, the higher the PR, the fullest the OD matrix will be and (ii) different LDC levels corresponding to realistic situations with incomplete loop detector data (either because of malfunctioning loop detectors, or because of intersections/lanes without loop detectors installed); this LCD will be used to complete and improve the former OD matrix. All the scenarios are randomly generated from the true and consistent values obtained in VISSIM. For each scenario, 500 random iterations are performed. Within each iteration, random vehicles and loop detectors are selected based on the hypothesis about data availability corresponding to that specific scenario.

The influence of the FCD-PR is evaluated by gradually increasing the FCD-PR by 5% on each step, from 5% to 100%. The influence of LDC is evaluated by gradually decreasing the number of available and properly working loop detectors by 10% on each step, from 100% to 0%. Hundred per cent means every entering and exiting lane has a loop detector. Notice that not all loop detectors are the same; some of them have a higher influence on data availability since they are related to more movements than others.

These variations in FCD-PR and LDC yield 220 different scenarios (20×11). For each scenario 500 random iterations are performed. After 500 iterations, the average error for a given scenario becomes stable, with relative differences between iterations below 0.05 percentage points. This was deemed to be appropriate for the level of detail required in this study. Each example below contains data from 110,000 tests. At a significance level of 5%, with this number of simulations, the results obtained will be within a range of $\pm 0.29\%$, while at a significance level of 1%, the range would be $\pm 0.39\%$.

4.1. *Example 1: Simple intersection*

Figure 4 provides a closer look at Location 1. It corresponds to the intersection of Borsenstrasse and Talstrasse streets in Zurich. In this intersection eight movements are possible (x_1, x_2, ..., x_8). They are presented in Table 3.

Since one loop per lane is installed, in this location we place a total of 10 loop detectors (indicated with numbers 1–10 in Figure 4) to obtain the complete number of vehicles entering and exiting the intersection, and associated with the individual movements in Table 4. In addition, as explained before, we use FCD for our calculations. Notice that unless we had enough redundancy data from loop detectors (i.e. significantly more loop detectors than movements) it would not be possible to estimate an OD matrix without additional information such as surveys, proportion of movements, a seed matrix, or longitudinal data. Recall also that not all loop detectors are the same (in Table 4 for example, loop detectors 10 and 6 appear in three movements each out of eight possible movements, while loop detectors 4 and 5 appear on two movements each, and loop detectors 1, 2, 3, 7, 8, and 9 appear only on one movement each).

The total data used in this example based on Location 1 (Figure 4) included 1626 vehicles. The results for the analysis are shown in Table 5 and illustrated in Figure 5. Evidently, the quality of the results (i.e. smaller errors) increases with data availability.

The absolute average error goes from 46% in the worst situation, with only 5% of FCD-PR and no loop detectors (0% LDC), to 0% when the FCD-PR is 100% and every lane of the network has a working loop detector. Notice that as the FCD-PR increases, the importance of the LDC decreases (e.g. for an FCD-PR above 80%, almost the same accuracy can be obtained with either 0% or 100% LDC). This is not surprising, as FCD can provide highly accurate information on OD matrices. So in reality, for this specific case, if the FCD-PR was higher than 80% it would be worthless to install loop detectors, as we could obtain less than 5% error independently of the number of loop detectors installed. In the extreme case of 100% FCD-PR, as one would expect,

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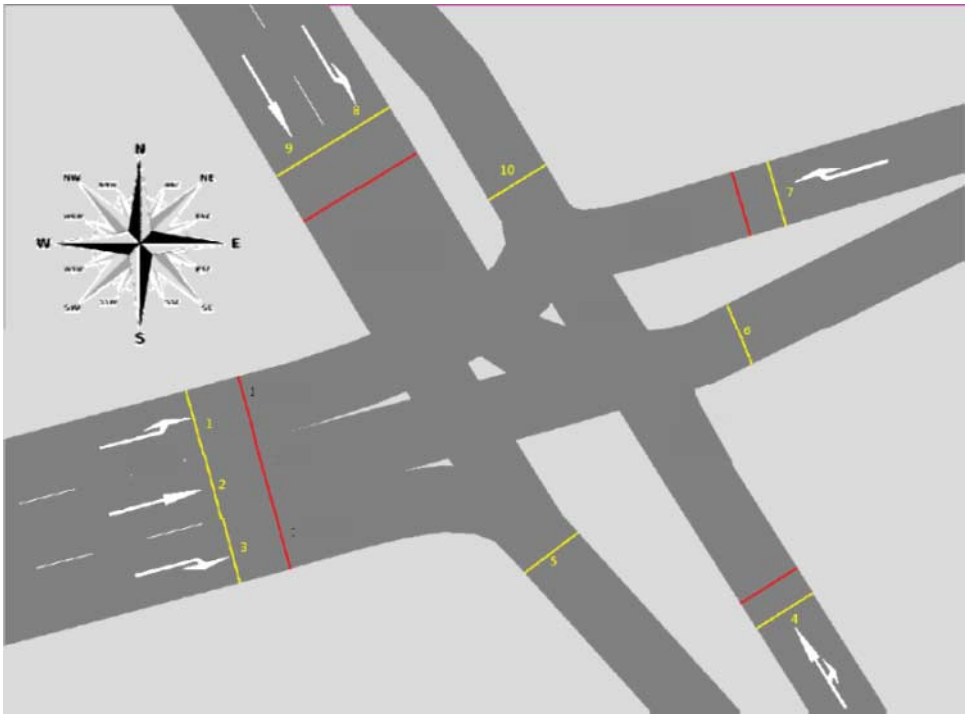

Figure 4. Location 1: simple intersection. Aerial view and diagram of intersection from VISSIM.

Table 3. OD movements for Example 1: eight movements allowed.

O/D	N	S	E
N	–	x_1	x_2
S	x_3	–	x_4
E	x_5	–	–
W	x_6	x_7	x_8

Table 4. Relationships between loop detectors and movements for Example 1.

O/D	N	S	E
N	–	Loop 9, Loop 5	Loop 8, Loop 6
S	Loop 4, Loop 10	–	Loop 4, Loop 6
E	Loop 7, Loop 10	–	–
W	Loop 1, Loop 10	Loop 3, Loop 5	Loop 2, Loop 6

perfect information is available and loop detectors are not necessary. On the other hand, loop detectors alone (100% LDC and 5% FCD-PR) fail to make predictions with less than 10% error. In Figure 5 there is a line dividing the combinations of FCD-PR and LDC that provide more vs. less than 10% error. It can be seen that the maximum FCD-PR required is 55% (for the case without loop detectors), and the minimum is 10% (for the case with 90% or more LDC). Given that the range is rather large, more complex examples are examined next.

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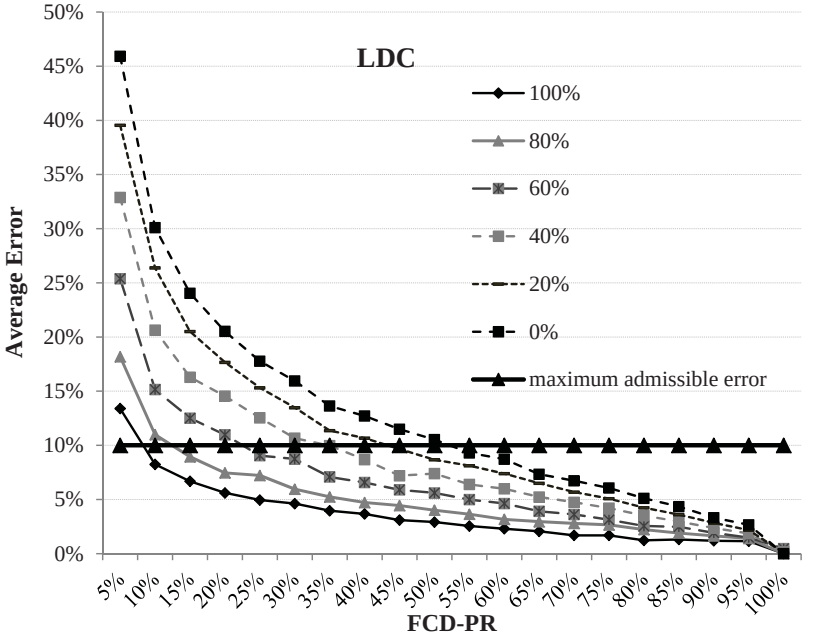

Figure 5. Results for Example 1: simple intersection. Penetration rate vs. average error depending on availability of loop detectors.

4.2. *Example 2: Network with 3 intersections and 18 movements allowed*

Figure 6 shows Location 2. It consists of three intersections connected by three streets. There are 14 loop detectors that can be installed, eight in the lanes entering the network, and six in the lanes exiting the network. Considering the perimeter of this network, and based on the real conditions, only 18 movements are possible. In order to simplify the explanation, capital letters have been chosen for naming the different origins and destinations. The allowed movements are shown in Table 6.

The total data used in this example included 1626 vehicles, same as in Example 1. The results for the analysis are illustrated in Figure 7.

A quick visual comparison between Figures 5 and 7 shows that the range of errors for any given FCD-PR is much smaller in Example 2 than in Example 1. This is due to the loop detector data redundancy in Example 1 (10 loop detectors covering 8 possible movements vs. 14 loop detectors covering 18 possible movements in Example 2). In other words, given the higher loop detector data redundancy from Example 1, results in that case are more sensitive to the lack of LDC. The smallest possible error for 5% FCD-PR is 31% in Example 2 (over twice as large as the 13% from Example 1). This smaller error in Example 1 is again due to its data redundancy. On the other hand, when zero loop detectors are available, the largest possible error in this example is 40% (smaller than the 46% from Example 1). This is due to the amount of total data. Recall that $I_{\text{mov}} \cup I_{\text{loop}} = I$ and the size of the dataset is the cardinal of I. Hence, since in Example 2 the number of movements considered is bigger than in Example 1, the size of the data set is also larger. This, evidently, affects the quality of the adjustment. Notice that the amount of data could be increased by adding movements, number of loop detectors, or by having a bigger data sample (i.e. number of vehicles). More details are provided in Section 5 (Figure 10).

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Table 5. Results for Example 1: simple intersection.

	Average relative error vs loop detector availability										
FCD-PR	**100%**	**90%**	**80%**	**70%**	**60%**	**50%**	**40%**	**30%**	**20%**	**10%**	**0%**
5%	13%	15%	18%	21%	25%	30%	33%	36%	40%	42%	46%
10%	8%	9%	11%	13%	15%	19%	21%	23%	26%	28%	30%
15%	7%	8%	9%	11%	13%	14%	16%	19%	21%	23%	24%
20%	6%	7%	7%	9%	11%	12%	15%	15%	18%	19%	21%
25%	5%	6%	7%	8%	9%	10%	13%	14%	15%	16%	18%
30%	5%	5%	6%	7%	9%	9%	11%	12%	13%	15%	16%
35%	4%	5%	5%	6%	7%	8%	10%	10%	11%	12%	14%
40%	4%	4%	5%	6%	7%	8%	9%	9%	11%	12%	13%
45%	3%	4%	4%	5%	6%	7%	7%	9%	10%	10%	11%
50%	3%	3%	4%	4%	6%	6%	7%	8%	9%	9%	11%
55%	3%	3%	4%	4%	5%	6%	6%	7%	8%	9%	9%
60%	2%	3%	3%	4%	5%	5%	6%	6%	7%	8%	9%
65%	2%	3%	3%	3%	4%	4%	5%	6%	7%	7%	7%
70%	2%	2%	3%	3%	4%	4%	5%	5%	6%	6%	7%
75%	2%	2%	3%	3%	3%	4%	4%	5%	5%	6%	6%
80%	1%	2%	2%	2%	3%	3%	4%	4%	4%	5%	5%
85%	1%	2%	2%	2%	2%	3%	3%	3%	4%	4%	4%
90%	1%	1%	2%	2%	2%	2%	2%	3%	3%	3%	3%
95%	1%	1%	1%	1%	1%	2%	2%	2%	2%	2%	3%
100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

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As before, when the FCD-PR increases, the importance of the LDC decreases. In this case, for FCD-PR above 75% it is worthless to install loop detectors, as we could obtain less than 5% error independently of the number of loop detectors installed. Here the FCD-PR required for an average error below 10% ranges from 25% (for the case with 100% LDC) to 45% (for the case with 10% or less LDC).

4.3. *Example 3: Network with 3 intersections and 30 movements allowed*

To further increase the complexity of the problem, in this example we still use Location 2, but create a fictitious set of true and consistent data that simulate all possible movements in this network (a total of 30, excluding those with the same origin and destination) (see Table 7). Loop detectors are considered to be the same as those in Example 2.

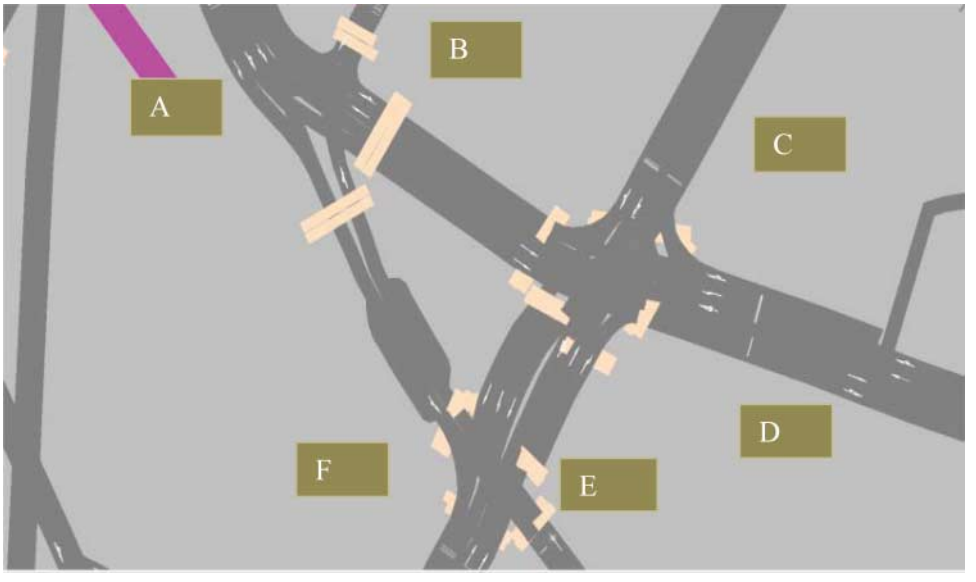

Figure 6. Location 2: network with three intersections. Aerial view and diagram of network from VISSIM.

Table 6. OD movements for Example 2: 18 movements allowed.

O/D	A	B	C	D	E	F
A	–	x_1	–	x_2	x_3	x_4
B	x_5	–	–	–	–	–
C	x_6	x_7	–	–	x_8	x_9
D	x_{10}	x_{11}	x_{12}	–	x_{13}	x_{14}
E	x_{15}	x_{16}	–	–	–	–
F	–	–	x_{17}	x_{18}	–	–

The total data used in this example included 3544 vehicles (over 200% the number considered in Example 2). The results for the analysis are illustrated in Figure 8.

In this case the range of errors for any given FCD-PR continues to decrease (e.g. for a 5% FCD-PR the minimum error is 37% and the maximum error is 41%). The reasons are the same as before: less data redundancy and more data in total.

Table 7. OD movements for Example 3: 30 movements allowed.

O/D	A	B	C	D	E	F
A	0	x_1	x_2	x_3	x_4	x_5
B	x_6	0	x_7	x_8	x_9	x_{10}
C	x_{11}	x_{12}	0	x_{13}	x_{14}	x_{15}
D	x_{16}	x_{17}	x_{18}	0	x_{19}	x_{20}
E	x_{21}	x_{22}	x_{23}	x_{24}	0	x_{25}
F	x_{26}	x_{27}	x_{28}	x_{29}	x_{30}	0

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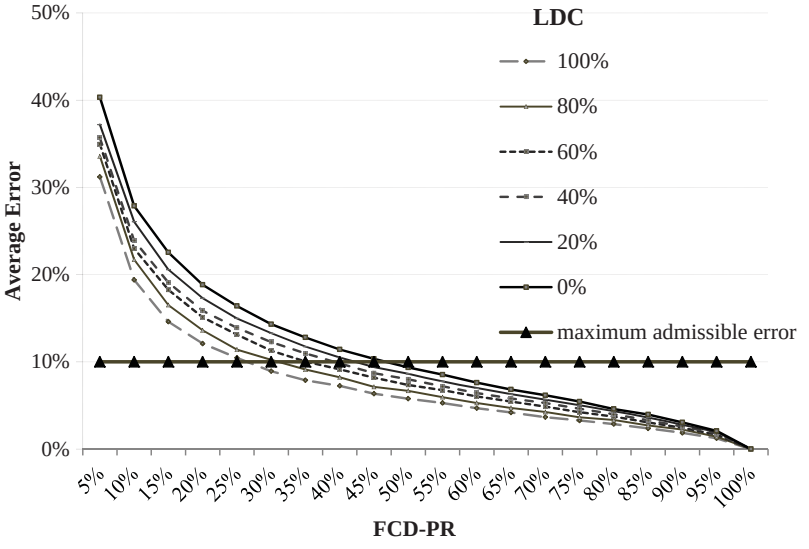

Figure 7. Results for example 2: network with 3 intersections, 18 movements allowed, and the same number of vehicles as in Example 1. Penetration rate vs. average error depending on availability of loop detectors.

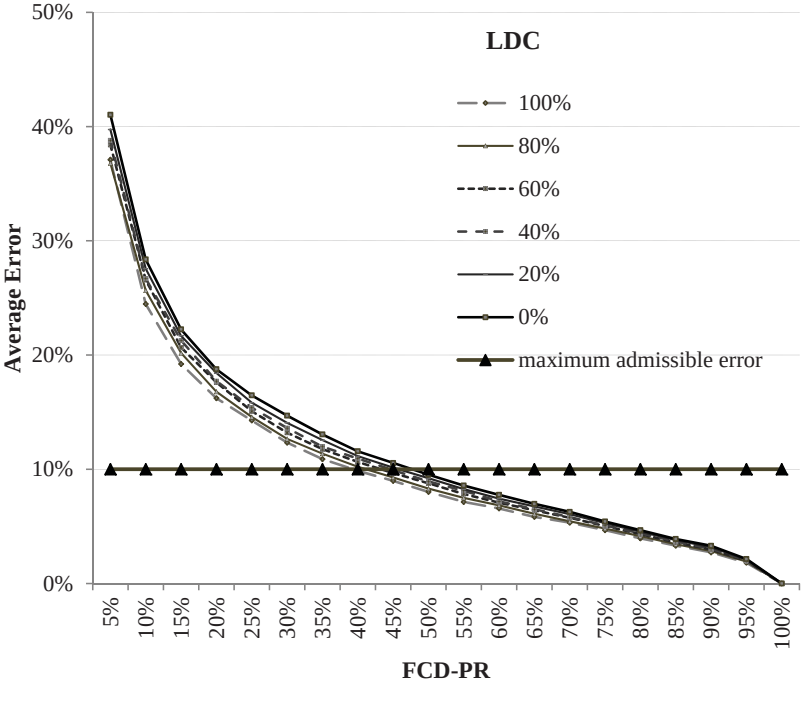

Figure 8. Results for Example 3: network with 3 intersections and 30 movements allowed. Penetration rate vs. average error depending on availability of loop detectors.

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The FCD-PR required for an average error below 10% ranges from 40% (for the case with 70% or more LDC) to 50% (for the case with 0% LDC).

5. Discussion and final remarks

In this paper we have:

- applied a new BO method for the estimation of OD matrices and
- evaluated the trade-offs between FCD-PR and LDC for different accuracy levels on the estimation of OD matrices.

The proposed methodology, based on a BO using fuzzy logic theory, not only has clear advantages over other existing methods (especially in terms of data requirements, computational complexity, and quality of adjustment), but was demonstrated to provide accurate results with low computational costs (ranging within (0.07, 1) seconds per simulation depending on the amount of data within every the scenario, for the examples provided in this paper). Other authors (Guozhen et al. 2011) have used the LSM to estimate dynamic OD matrices. It is not possible to compare specific results because data are not explicit in the former work. However, the relative errors for different FCD-PR are shown, considering in all cases 100% LDC (or link flow measurements); and for their highest FCD-PR (i.e. 90%), they get a relative error of 2.62%, equivalent to the relative error we get for this same FCD-PR but 0% LDC.

The BO method was illustrated with three examples covering two different locations in the city of Zurich. The three examples examined different levels of data redundancy (possible movements vs. maximum possible number of loop detectors), data size (total number of vehicles), area size, and network complexity (number of movements allowed).

To validate the method for different data availability levels, and to generalise the results, each example was studied under 220 scenarios (combinations for FCD-PR and LDC), and each scenario was evaluated with data from 500 random iterations. The goal was to emulate: (i) different FCD-PR and (ii) different LDC levels corresponding to realistic situations with incomplete loop detector data (either because of malfunctioning loop detectors or because of intersections/lanes without loop detectors installed).

The main findings from the three examples are summarised below:

(1) The minimum FCD-PR required to ensure an error smaller than 10% is very case specific. Figure 9 shows the data from the three examples combined. The minimum FCD-PR goes from 10% when 100% of loop detectors are available, to 50% when the LDC is 0%. That minimum FCD-PR does not vary much as a function of the LDC for Example 3 due to the lack of data redundancy (see points 3 and 4). Hence, on average, if loop detectors cover 30% of the lanes, a 40% FCD-PR should be enough to provide an OD matrix with an admissible error. In cases where the redundancy is really high, a lower FCD-PR should be possible.

(2) For any given combination of FCD-PR and LDC, the resulting error in OD estimation is affected by the data redundancy in the network (i.e. the number of possible movements per maximum possible number of loop detectors), and the total data available (i.e. total number of vehicles counted by both FCD and loop detectors).

(3) The error for high levels of LDC increases as the data redundancy in the network decreases (i.e. the error increases as the number of possible movements per loop detector increases). See maximum values for the bottom lines (e.g. 100% LDC) in Figures 5, 7, and 8. This is not surprising, as, especially in large networks with low redundancy a high level of LCD, we cannot reduce the error without some additional information on route

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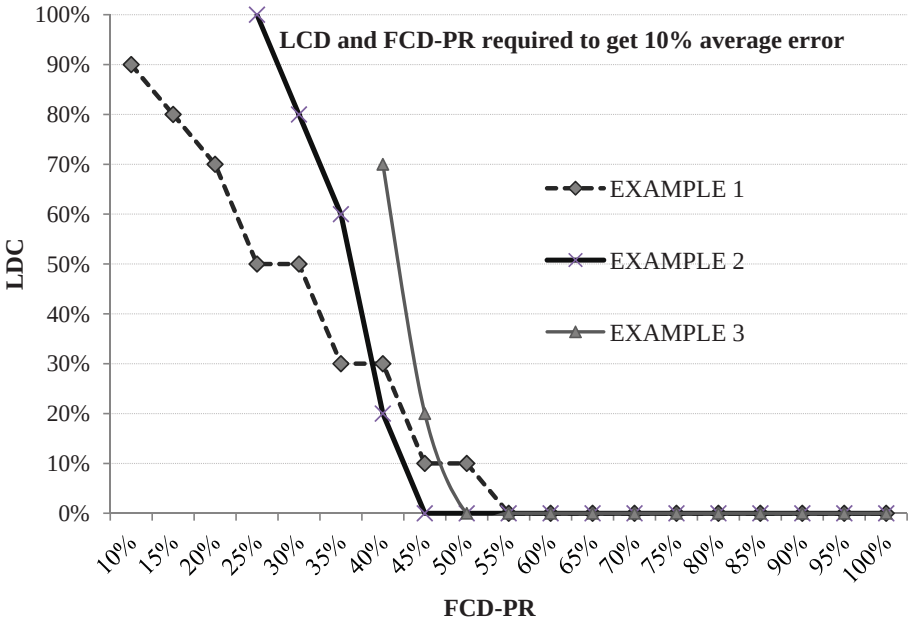

Figure 9. Combination of LDC and FCD-PR required for ensuring an average error below 10%.

choice. Hence, for networks with very low redundancy (due to a high number of possible movements), it might not be worth to invest in a high LDC (notice how in Figure 9, for Example 3 a higher LDC does not imply a lower FCD-PR). Whereas in networks with just a few movements, a high LDC can provide fairly accurate OD matrix information (see line for Example 1 in Figure 9).

(4) Similarly to point 3, the FCD-PR required for any given accuracy levels generally increases as the data redundancy in the network decreases. The differences are especially noticeable for high levels of LDC. See the slope of the bottom lines in Figures 5, 7, and 8.

(5) The error decreases as the size of the data sample increases (assuming the redundancy remains more or less stable). When the network stays the same, as well as the number of movements and loop detectors, the amount of data could be increased by considering a bigger quantity of vehicles. Figure 10 shows the results (for the sake of simplicity only 100%, 50%, and 0% of LDC are presented) for two different sets of data in Example 2. One set is the same as that used in Section 4 and includes 1626 vehicles. The other set (i.e. more data) includes 2735 vehicles. Note that everything else remains the same, including the redundancy (i.e. number of movements and loop detectors). It is evident that increasing the amount of data alone reduces the error, especially for lower levels of FCD-PR. This is not surprising, as the amount of data clearly influences the estimation process in any probabilistic analysis.

(6) The importance of LDC decreases as FCD-PR increases. In other words, as the FCD-PR becomes higher, the differences between errors associated with different levels of LDC become smaller. See Figures 5, 7, and 8.

Even though here we have evaluated three networks of two different sizes, one question remains: what would happen to this methodology as the network size increases even more? Evidently, that poses additional complexities because:

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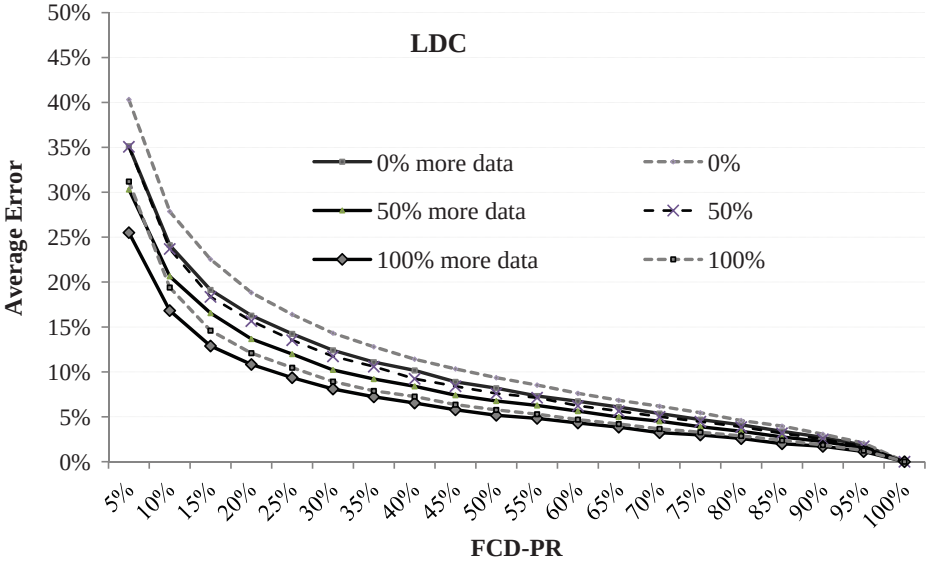

Figure 10. Comparison between two data sets of different sizes for Example 2.

(a) The total number of possible movements could increase.
(b) The total number of entering and exiting lanes into the network could increase.
(c) Some trips might start or finish inside the network, and this would invalidate our flow conservation equation.

Changes (a) and (b) will obviously increase the number of variables and constraints, which will make the problem more complex, increasing its computational cost. However, the problem will remain feasible since the real solution will still be contained within the set of valid solutions.

Change (c), however, will require adding new possible movements (e.g. 'stay inside'). For that, we might consider 'neighbourhoods', i.e. stay inside neighbourhood A, B, C, ... adding as many origins/destinations as neighbourhoods are considered. This would increase the number of variables, driven by an increase in the number of movements and maybe loop detectors (as the adjustment would need sufficient loop detectors strategically placed for providing enough data to obtain a good solution). Notice that communication between neighbourhoods can occur at several places, so there could be more than one entry/exit to each neighbourhood. In any case, the problem, as before, would remain feasible, and the methodology would not change.

For each of the three examples presented in this paper, we estimated a unique (static) OD matrix. Nonetheless, the proposed methodology is equally applicable for the estimation of dynamic (temporal) OD matrices, as they are typically represented by a sequence of sub-matrices, each one representing a time interval. The only constraint here would be the amount of data available as the time slices become too thin.

The possibility of estimating the OD matrix from the combination of loop detectors and FCD is highly promising. From an operational point of view, it allows us to create real-time dynamic OD matrices for traffic management purposes (e.g. ITS measures), while taking advantage of the useful and powerful positioning devices that have been gaining popularity in the last few decades. From a planning/design perspective it allows us to better understand demand patterns

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and their variations (spatially and temporally). Lastly, from an economic point of view, understanding the trade-offs between data from loop detectors and FCD could lead to the optimisation of investments in resources for data collection.

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