

BRIDGING AGENT- AND TRIP-BASED DEMAND MODELS FOR MULTIMODAL OD ESTIMATION: A REVIEW AND CONCEPTUAL IDE FRAMEWORK

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Abstract: Understanding multi-modal travel demand is essential for traffic management and transport planning. However, estimating time-dependent origin-destination (OD) flows remains challenging, when direct observations are limited and different transport modes (vehicles, cyclists, and pedestrians) influence each other. While numerous OD estimation methods exist, most treat modes separately and rely heavily on traditional surveys or historical matrices, often unavailable or incomplete. This paper presents a non-systematic review of existing approaches to offline dynamic OD estimation and proposes the Integrated Demand Estimation (IDE) framework for multi-modal offline dynamic OD. This framework integrates the disaggregate behaviour of agent-based models with the stability and computational efficiency of trip-based demand models. The framework is designed to generate an initial multi-modal OD matrix using synthetic population methods and iteratively adjusts it using observed traffic counts, travel times, link popularity, terrain characteristics, and GTFS data. By explicitly accounting for the interactions between motorised and vulnerable road users, the framework aims to improve the consistency and realism of OD estimates for vehicles, cyclists, and pedestrians. It addresses literature gaps regarding limited non-motorised data and fragmented multi-modal treatment. The framework is intended to support urban digital twins, provide a basis for multimodal simulation inputs, and help planners understand multimodal travel patterns for sustainable mobility and infrastructure design.

Key words: *Multi-modal OD estimation; Agent-based modelling; Trip-based demand modelling; Route choice; Travel demand; Traffic assignment*

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1. Introduction

Travel demand patterns are essential in various traffic analysis contexts such as traffic management, policymaking, and other evaluations that use traffic simulators

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[6]. Often, decision-making processes are based on traffic models, which require an understanding of travel demand across space and time, including the origins, destinations, and possibly routes of trips. Good traffic simulation outcomes rely on high-quality data [110].

Due to the difficulty in observing everyone's origins, destinations, and routes firsthand, creators of traffic models estimate time-dependent Origin-Destination (OD) flows and trips based on available data, which is still a challenge [62]. Fig. 1 illustrates the OD estimation problem using a simple network representation. Directed links connect nodes, v_i, and different parts of a region are represented as zones, z_i. Traffic originates, q_i^{out}, and terminates, q_i^{in}, at the centroids of these zones (i.e. at the nodes). An OD matrix thus defines the travel demand, $T_{(O,D)}$, between every pair of zones, for example from $v_1 = O$ to $v_4 = D$. Assigning these OD trips to the available routes, a process known as traffic (or trip) assignment [1], yields the traffic volume on each transportation link, q_j, and allows traffic volumes and travel times to be estimated as functions of network characteristics [98].

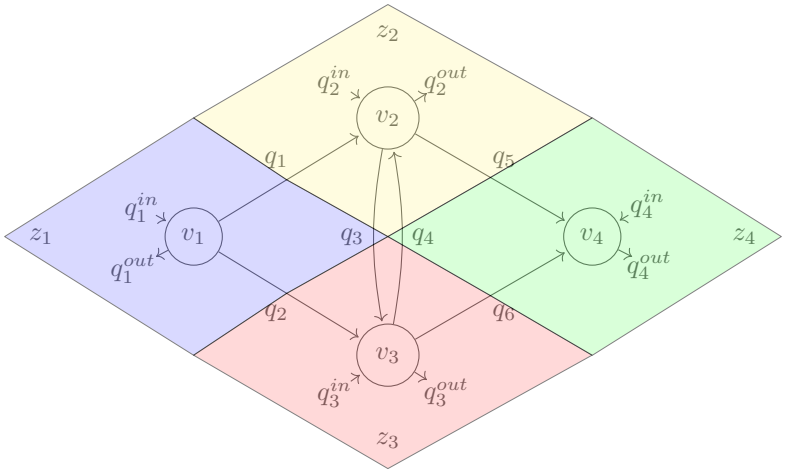


Fig. 1 *Example of a road network. Reproduced from [138].*

OD estimation and traffic assignment are common steps within traditional trip-based demand models, the most widely applied of which is the Four Step Model (FSM) [78]. As illustrated in Fig. 2, the FSM stages are analysed separately, in sequence, as an input-output pipeline, each performed by mathematical or statistical methods. According to [80], the inputs are a transport system, typically a network such as the one in Fig. 1 whose links and nodes have attributes (e.g. length, turn prohibitions, capacity), and an activity system, represented by socio-economic, demographic, land-use, and building-stock data plus other factors influencing travel behaviour. The FSM steps are:

1. Trip Generation: determines trip frequency and propensity to travel (usually according to socio-economic, building, and land-use characteristics), resulting in origin of trips.

2. Trip Distribution: trips are distributed to match trip attraction, considering travel impedance such as travel time and travel cost, thus defining the destination of trips and outputting OD trip matrices that define OD flows.

3. Mode Choice: OD trip matrices are adjusted to show proportions of trips with different travel modes (modal OD trip matrices).

4. Route Choice: modal OD trip matrices are assigned to mode-specific networks and route decisions are made considering mode-specific performance measures, calculating mode-specific flows on links and route travel times.

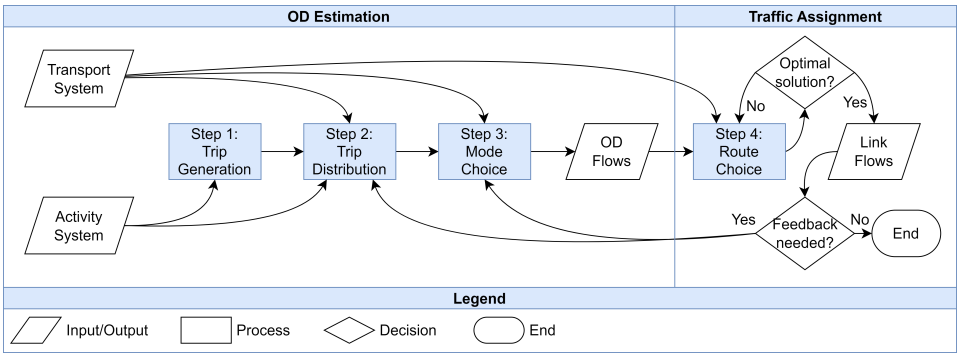


Fig. 2 *The Four-Step Model. Adapted from [80] (p. 39).*

In urban areas, pedestrians have right of way over motorised vehicles at designed areas such as pedestrian crossings and places with traffic-calming measures. Cyclists tend to avoid unpleasant places or spaces where they feel unsafe (subjective feelings connected to the amount of vehicles passing them and a sense of crowdedness [135]). Thus, in this study, we considered these three transport modes (motorised vehicle, pedestrian movement, and cycling modes) together, leading to a model that can improve urban mobility planning and traffic management in urban areas with mixed transport modes. Although public transport is an important component of urban multimodal travel, it is not modelled as a separate demand mode in the current version of the IDE framework. The present study focuses on the interactions between motorised road users, cyclists, and pedestrians, particularly where these modes share or interact with the road network. Public transport is instead represented through GTFS data, which contribute primarily to the estimation and calibration of pedestrian demand.

Given the distinct characteristics across road user types, each group was modeled individually based on the available data. Data availability remains a notable obstacle for vulnerable road users [64]. For instance, cyclists, who can be counted with road detectors [60], typically choose their route not simply based on shortest/fastest route because many other factors come into play [95]. This holds true for vehicles and (at some extent) pedestrians as well. Vehicles can be easily detected by induction loops that are widely used on roads, but counting pedestrians can be problematic when they are partially obscured, stop, and form groups (e.g.

when waiting to cross a street or to for public transport to arrive) [115]. Bicycle and pedestrian activity data at the neighborhood level are generally limited or even unavailable in many areas [108].

Although previous research has dealt with OD estimation and traffic assignment for motorised and non-motorised trips, previous approaches do not account for the interaction of modes on the road. In Section 2, we show that typical approaches use mode splits to estimate OD flows and then approach the assignment task separately for each transport mode. While some research has considered the integration of travel demand estimation taking vehicular road users and vulnerable road users (pedestrians and cyclists) into account in a single framework (see Section 2), most use agent-based modelling (ABM). To address this gap, we propose a single framework that combines agent-based models with traditional trip-based demand models in order to better account for the influence of different transport modes. The proposed framework is also intended to calibrate final OD matrices using available measured observations.

Contributions

This paper makes the following contributions:

- We provide a structured, non-systematic review of offline dynamic origin-destination (OD) estimation methods across motorised and non-motorised transport modes, highlighting methodological gaps in multi-modal integration.
- The main contribution is the Integrated Demand Estimation (IDE) framework, which synthesises the theoretical gaps identified in the literature with the empirical challenges observed in our traffic survey. The framework combines an agent-based modelling (ABM) methodology, which estimates a prior OD matrix, with a traditional trip-based demand model, which adjusts this sampled (i.e. prior) OD matrix, within a single multi-modal pipeline for offline dynamic OD estimation in intervals shorter than a day.
- Within the IDE framework, a mode-specific calibration strategy captures the influence of transport modes on one another and explicitly accounts for the interactions between motorised vehicles and vulnerable road users (VRUs; pedestrians and cyclists). The proposed strategy combines traditional traffic information from typical research sources with the addition of non-typical data sources, aiming at a more realistic and consistent estimation of multi-modal urban demand.
- Through an empirical multi-modal traffic survey, we identify systematic observability gaps in traditional traffic data, and show how these empirical findings inform the design and structure of the IDE framework. The survey serves as an empirical diagnostic rather than a validation of the IDE framework.

2. Literature Review

This section reviews the literature on OD estimation for three modes of transport and identifies research gaps that can be successfully bridged with the Integrated Demand Estimation (IDE) framework for multi-modal offline dynamic OD, hereafter referred to as the IDE framework.

The estimation of OD matrices is a very common action in traffic modelling and can take place offline (for medium- to long-term planning and design) or online (for the design of real time traffic management systems) [23]. These methods can be classified according to their temporal demand dynamics, i.e. steady state (static) or time dependent (dynamic) matrices [33]. In dynamic OD estimation, the estimation of matrices is used to find OD flows that fit traffic observations for either within-a-day or day-to-day, time-dependent intervals. In sequence estimation, the estimated demand of one interval is used to estimate the next interval. Meanwhile, for a simultaneous estimation, OD flows are estimated all at one time. According to [93], the estimation of matrices is a highly undetermined and thus highly non-convex problem. Because of this, assumptions are often made based on generated trips in order to minimise the number of variables, improve computational performance, and reduce the noise of uncorrelated measurements.

Generally, OD matrices for larger networks are already available for cities or districts, with macroscopic models having been used to obtain them. However, for smaller study areas and for microscopic traffic modelling, travel demand between OD pairs must be estimated, usually using traffic counts [110]. Estimating travel demand using direct measurements, interviews, or surveys is difficult and often costly. Thus, aggregate methods use motorised vehicle traffic counts and other available information to obtain reasonable estimates [1]. Some researchers, such as [9], have performed OD estimation without any data having been observed.

Nevertheless, capturing demand patterns for traffic assignment may lead to errors when choices regarding departure time and destination are available. In such cases, traffic counts and other network-based measures can fit the measurements used to update a prior estimate [23]. Estimating travel demand (e.g. calculating OD flows and assignment of trips to each possible route) for different modes of transportation involves different data sources, methodologies, and pre-processing techniques depending on the characteristics of the mode. Below, we discuss different methods for within-a-day and offline OD estimation, as our approach (Section 4) is intended for mobility models with intervals shorter than a day.

2.1 OD Estimation for Vehicles

Many approaches have been proposed for solving the OD estimation problem for vehicles because the topic is widely studied. In general, aggregate methods find an OD matrix, which reproduces traffic measure observations such as traffic counts. Dynamic OD estimation methods based on traffic counts can be classified according to network performance (i.e. congested or uncongested) [33]. Furthermore, as activity-based models can be coupled with traffic simulation, as in [87], traffic counts have been used just to adjust the demand estimation from disaggregate travel behaviour in activity-based models.

Regarding data, [6] pointed out that selecting other data about traffic parameters can be also used, e.g. speeds [17, 28] and travel times, and even densities/occupancies [34]. [29] analysed the impact of using different types of information for estimating dynamic OD flows, bringing attention to sampling of path travel time measurements, speeds and flows. The integration of route turning rates by [119] also showed how such metrics could be used together with flow data with the dynamic OD demand estimation problem, also explored by [132]. License plate surveys are challenging to conduct manually for a large number of vehicles. However, video recordings combined with manual transcription and probability matrices can be an effective and flexible solution for ensuring high-quality OD matrix results [110]. Automated vehicle identification technologies are alternatives for prior sampled OD matrices (e.g. travel surveys, prior estimates, historical matrices) and useful for probe trajectories, since they enable sampling OD travel times, OD route proportions, and OD flows [7, 85, 96, 118, 128, 131, 134]. Types of vehicle identification techniques include floating car data [18, 86, 93], bluetooth detection [84], and license plate recording [103, 110, 132]. [103] estimated OD matrices solely using probe trajectories reconstructed by a particle filter model. [131] sampled probe trajectories to avoid sophisticated traffic assignment methodologies. An example of such sophisticated methodologies is presented by [72], who developed a path flow-based optimisation model that solved both OD demand estimation and traffic assignment. Simultaneous routes and departure times were considered together with elastic demand in a mesoscopic traffic flow simulation framework to represent traffic dynamics, such as queues and spill back and to capture the impact of shock waves. Their final solution was compared to traffic observations (e.g. link flows and densities) to add penalties to be minimised during optimisation. Socioeconomic data (e.g. census data) could facilitate integration of trip-generation, trip-attraction and trip-distribution into one model, as demonstrated by [100] and [58].

Traditional entropy maximisation for OD estimation utilises traffic counts with a minimum assumption [10, 34], though other available data can be used to make it more flexible. Methods for uncongested networks assume that link travel times can be computed from the network model, even at links where flows are not measured. In such cases, estimates of trip proportions between origin and destination zones aim to minimise the "distance" (i.e. the difference) between estimated and measured flows, explored by [50, 136]. Some attempts have been made to solve the problem using statistical models (e.g. [58]), where Bayesian inference was used to improve an initial OD matrix generated by a gravity model containing socioeconomic data.

Although most applications aim at finding an optimal solution for route choices according to predefined criteria (e.g. travellers trying to minimise travel costs), others, with resultant link flows, provide feedback to trip distribution models and/or mode choices, which leads to better results. For the case of congested networks, link flows also depend on travel times, route choice rates, and assignment proportions. The issue with congested situations is that usually, neither travel times nor flows are known for all links in a network. Therefore, a traffic assignment model is needed to estimate these metrics, which also depends on an OD matrix. However, this creates a problem of circular dependence between OD matrix estimation and

traffic flow assignment. A bilevel programming approach is one of the possible solutions to this problem. The upper-level problem uses statistical techniques to select the most appropriate OD matrix, while the lower-level choice is to use deterministic or stochastic user equilibrium models to determine route choice proportions that fit with estimated OD flows [33, 75]. Efforts have focused on combinations of the entropy maximum model, e.g. [43] utilised a user optimal assignment model using a variational inequality formulation (also employed by [92]), while [127] integrated least squares to account for elastic demands, and [126] included iterative algorithms to adjust path costs during traffic assignment. Moreover, heuristic iterative algorithms are also proposed by [130, 129]. In particular, [111] introduced a heuristic-iterative linear programming approach and compared it against other maximum entropy and bilevel programming approaches. Their approach decomposed the OD pair flow into subproblems to find the "shortest" path between OD pairs while minimising the difference between observed and calculated link flows and determining missing link volumes to satisfy user-equilibrium. Later, [46] and [48] used fuzzy logic to extend this approach to a prior OD matrix, where traffic counts were incomplete and imprecise. In contrast, ([116]; large networks), [37] and [74] proposed gradient descent approaches, providing methods that outperformed the gradient descent approach. Other approaches assume stochastic user equilibrium [19], and the bilevel problem was converted into a single-level problem by [44] using a marginal function in their coordinate descent approach. An adaptation to the known approach for Dynamic Traffic Assignment, Simultaneous Perturbation Stochastic Approximation (SPSA), was introduced by [28]. This approach used a gradient approximation to find a good solution while assuming that the initial OD matrix was "near" the optimal one and extendable to census data and sample information. [38] used a signalised path-based cell transmission model using a non-linear mathematical programme, where traffic flow dynamics were used to estimate OD demands given link counts and traffic light plans, resulting in lower estimation errors than the traditional approach for both uncongested and congested scenarios.

Other models focus on the application of statistical inference methods, where traffic counts can be combined with a prior sampled OD matrix and have the advantage of accounting for distribution of the input data. In general, the most common approaches are maximum likelihood estimation (MLE) [22, 70, 96, 117], generalised least squares (GLS) [10, 20, 131] with [23] proposing quasi-dynamic OD pairs to reduce the unknown OD pairs and Bayesian inference [58, 66, 76, 77]. The quasi-dynamic OD pairs approach was extended to work without a prior OD matrix by [10], who combined least squares estimation with the traditional entropy maximisation method. The GLS approach was also applied by [17] to estimate OD matrices from estimated link flows and historical OD matrices, and together with fuzzy optimisation by [14], who included uncertain starting demand values with link flows estimated from a prior distribution of vehicle speeds by using Bayesian inference. Other notable approaches have used stochastic traffic assignment simulation [45] and non-linear least squares [134], of which was also explored with gravity and opportunity models [117]. [36] and [27] pointed out that previous works not only needed traffic counts but also prior information about every possible OD flow on a road network such as a routing Markovian chain method that calculates the proportion of incoming traffic likely to travel through certain link for

routes while a traffic simulator accounts for traffic characteristics. Furthermore, [132] and [27] proposed Bayesian network models. The latter considered the level of total traffic flow and its variability as well as the traffic flow conservation law, where only a prior link flows and observed were used as input. Among Machine Learning approaches, [105] solved the OD estimation problem solely with Artificial Neural Networks (ANN) by minimising a nonlinear function of calculated and observed link flows using the Damped Least Squares method. In order to tackle the problem of local optimal in traditional approaches, [128] used an ANN to train their model using probe trajectories and link flows, and then an Entropy Maximisation method using the best inference distribution from the ANN model to minimise calculated and observed flows.

2.2 OD Estimation for Cyclists

Cycling and walking offer environmentally-friendly transport modes that serve as alternatives to using cars [73]. However, concerns about safety risks, such as accidents, may impact the decision to walk or cycle for individuals who are cautious about taking risks, reducing the use of non-motorised travel as an alternative to driving [73]. Predicting the behaviour of vulnerable road users like pedestrians and cyclists is essential for ensuring safe and smooth traffic flow [41]. Therefore, in urban areas, the movements of vulnerable road users need to be examined. This is essential in terms of traffic management. As the use of bicycles in urban communities increases, this becomes a pressing issue that needs to be assessed when calculating travel demand. Monitoring the mobility patterns of cyclists in smart cities is crucial for the development of future bike-oriented transportation systems [90]. Understanding how bicycles interact with vehicles and pedestrians is crucial for the development of mixed traffic flow simulation models [133]. Thus, there is a need to examine and analyse the movements of bicycles, where it is important to gather accurate OD matrices of bicycles to support transportation planning and accommodate the growing demand for bicycles.

Bicycles have different travel patterns and speeds compared to motorised vehicles, making it necessary to consider these factors when estimating OD matrices. Additionally, cyclists may not always follow traditional roadways, as they tend to choose bicycle paths and lanes over the shortest possible routes, highlighting the significance of well-established bike infrastructure in cities [61]. Moreover, bicycle data may not be as readily available or easily captured compared to other modes of transportation. Therefore, gathering accurate and representative data for bicycle movements can be challenging.

Micro-mobility services have become increasingly popular in recent years, becoming a relevant part of the transportation network [63]. Bike sharing systems are one type of service; GPS data collected provides information on the start and end points of bike trips. This is one common source of data and can be used to estimate OD matrices for bicycles, and increasing usage makes this data more significant. [63] proposes algorithmic approaches (such as Support Vector Regression and Random Forest regressor) for analysing bike sharing system usage data, addressing challenges such as exceptional usage patterns and the impact of exceptional events such as COVID pandemic measures. [16] presents an analysis of the cycling flow between origin and destination for dockless shared bicycles.

To determine the predictable pattern of bike movements, several approaches have been suggested: e.g., primary OD demand in a gravity model and adjustment of primary OD trips using the Path Flow Estimator [106] and extraction of main components from an OD matrix using Singular Value Decomposition [16]. [39] introduced a model for estimating peak-period cyclist counts based on trip-generation and attraction factors, using actual cyclist-count data. The study involved organising data collected and assessing the suitability of roadway conditions for cycling. Information used to generate demand was sourced from a variety of channels, including interviews, surveys, literature, statistics, and logistics providers [91]. Some researchers prefer direct observations to ensure the reliability of information [91]. A model for simulating the demand for goods' deliveries by cargo bicycles in regions where motorised traffic is restricted is presented by [91], who used a modified four-step approach. [106] introduced a two-stage method for estimating bicycle demand, refining the results with observed data to enhance accuracy.

2.3 OD Estimation for Pedestrians

Estimating pedestrian OD matrices is crucial for traffic modelling and control, as it enables identifying optimal paths for travelers [62]. Additionally, obtaining these matrices is also necessary to understand pedestrian demand [26]. Pedestrians are more vulnerable than drivers because they are smaller, aren't protected, and are slower than motorised vehicles [51]. Motorised traffic variables such as noise and vehicle speed negatively impact how pedestrians perceive their route environments, with vehicle speed being an important factor [4]. Such factors make pedestrians susceptible to accidents and injuries. Pedestrian and bicycle mobility also differ, with pedestrians being more affected by temperature, precipitation, and time of day than cyclists [13]. These differences suggest the need for tailored approaches to plan pedestrian and bicycle mobility.

Pedestrian OD matrices can be estimated using video recordings and manual traffic counts that provide data for microscopic traffic modelling [110]. Different methods can be applied to obtain the matrices: optimisation-based cost-effective methodology [59], and agent-based pedestrian flow modelling [71]. Traditionally, the estimation of the OD demand matrix for pedestrians involves conducting surveys to gather data, followed by the calibration of the activity/destination choice model's parameters [26]. This survey approach, though widely used, faces some challenges and limitations. According to [2], three survey methods were considered: video monitoring, questionnaire surveys, and manual counting. While video monitoring was reliable and efficient, concerns over passenger privacy and data processing made it unacceptable for use. Questionnaire surveys raised issues of sample bias. As a result, the manual counting method was adopted, despite the challenges in a crowded environment. As a promising alternative to traditional survey-based approaches, the proposal by [113] uses Bluetooth and WiFi technology to estimate OD demands, in addition to station wait-times of transit riders in major metropolitan areas. By equipping turnstiles with detectors, unique device MAC addresses can track riders anonymously, providing low-cost and valuable information for transit agencies to improve operations and reduce delays [113].

2.4 Integrated OD Estimation

The integration of travel demand estimation considering vehicular road users and vulnerable road users (pedestrians and cyclists) into a single framework is increasing. Our prior work, [138], provided an initial study regarding OD estimation for each mode separately, i.e., vehicles, cyclists, and pedestrians, which illustrated a crucial weakness regarding data quality for estimating travel demand between an OD pair. Building on this, this paper significantly extends the initial study by providing a comprehensive review of multi-modal OD estimation, conducting a multi-modal traffic survey to identify empirical observability gaps, and a detailed discussion of the IDE framework.

Regarding the integration of OD estimation for all road users, typical approaches use mode splits to estimate OD flows and then approach the assignment task separated for each transport mode [123, 40, 68, 114, 3, 11, 15], or create networks that account for intermodality [82, 120, 121, 65, 83, 67]. Previous studies emphasised the importance of integrating diverse road users into transportation models. For instance, an adaptation for the simulation software MATSim [122] was introduced by [135], where not only attributes of road geography and infrastructure were considered, but also the number of cars and bicycles. Moreover, [49] stated that transport policy has become increasingly influenced by people's participation in certain activities at specific locations and times.

Activity-based models are becoming popular as traditional trip-based demand models; the inability of activity-based models to represent the reason of travel demand for all individuals in a household, besides the explicit representation of time-space constraints, presents a challenge. A further limitation of the activity-based models is that they generally do not capture interactions between traveling agents, such as interactions between motorised vehicles and cyclists [55]. Agent-based simulation models, such as MATSim [122], address this by simulating city-wide agent interactions.

Several methods have also been proposed to address the limitations of both trip-based and activity-based approaches. [81] accounted for trip chains in traditional trip-based demand models. Other methodologies include rule-based models [8], supernetworks [102], and use of the Household Activity Pattern Problem (HAPP) [88]. HAPP is a constraint-based subproblem within the activity-based modelling framework, used to ensure consistency at the household level during the activity modelling process. In addition to these methods, the use of synthetic population generation for simulation models [42, 99, 31, 56, 107, 52, 137] is also increasingly popular.

2.5 Summary and Literature Gaps

Having surveyed the literature, we decided to focus on the offline dynamic OD estimation problem, in which a mode-specific OD matrix was estimated for shorter intervals (e.g. within a day). Offline methods simultaneously estimated demand and supply model parameters, instead of simply updating, in real time, both parameters from baseline estimates [5]. The offline dynamic OD estimation problem was first formulated for vehicles by [21]. In their work, a statistical framework using the Generalised Least Squares (GLS) method was proposed for two-part op-

timisation. The first part of the optimisation measured the difference between the estimated OD matrix for an interval and a prior (e.g. historic) estimate of the OD matrix for that interval. The second part calculated the difference between measured link volumes and those predicted by the model.

The main issue of the two-part optimisation approach proposed by [21] is the need for a prior OD matrix, which represents an initial solution to a problem that is highly undetermined and highly non-convex [93]. Usually, this kind of prior OD matrix is based on historical estimates and surveys. However, in the absence of such data, an alternative is necessary for estimating the prior OD matrix. One methodology stands out due to its versatility and ability to include all transport modes: ABMs assume that people travel to participate in activities that are influenced by spatial, temporal, interpersonal, and accessibility interdependencies, following the principle of modelling each individual at a personal level to produce detailed information for each trip. Additionally, instead of generalised centroids as in macroscopic approaches, ABMs usually provide OD points as precise coordinates [12, 35]. We sought a prior OD matrix to act as an initial solution to our optimisation problem. The Eqasim framework, introduced by [53], was used to create synthetic travel demand for the agent-based MATSim model [122] from raw data (e.g. census data, household travel surveys, and other geographic datasets). Later, we extensively modified the Eqasim framework and extended it [99], to account for the availability of regional data in Ústí nad Labem, a city in the Czech Republic. Considering that our methodology was localised for this region, our process started by estimating a prior OD matrix using the synthetic population generation methodology for Ústí nad Labem.

Another issue in the two-part optimisation approach is that since the number of OD-pairs usually exceeds the number of links with measurements (e.g. traffic counts), there are usually many different OD matrix alternatives that reproduce observed measurements. Thus, we had to choose the most likely (or the best) OD matrix that fit [1] measurements. For instance, in the study by [112], a path generation algorithm first solved a restricted problem given an initial choice of a set of OD paths, then the problem was iteratively extended to find time-dependent shortest paths until the paths did not change. Although the general principle of our proposed single framework was the minimisation of the differences between link estimations and observations as well as travel impedance, a specific approach for each transport mode was necessary. Integrating each separated model allowed for a comprehensive analysis of travel behaviour and ensured that the needs of pedestrians, cyclists, and drivers are taken into account.

Pedestrian crossings have an impact on vehicle traffic, resulting in variable vehicle queues, delays and difficulties [24]. At mid-block crossings, some vehicles yield to pedestrians who are already at a crosswalk, while other pedestrians use a forced gap to cross the road. Such pedestrian behaviour impacts the flow of vehicular traffic [97]. The pedestrian forced gap condition affects the overall travel time for drivers in that area [57]. Therefore, we must first assign routes to pedestrians, and then these routes can be used for the OD estimation of vehicles.

Research about cycling often mentions the perceived risk of traffic as a common reason why people choose not to ride bicycles [109]. This perception of traffic risk has a negative impact on both potential and occasional cyclists' decisions to cycle

[109]. Cyclists encounter conflicts with vehicles and pedestrians at intersections without signals, impacting their ability to navigate these situations, but the specific behaviour of cyclists in conflict scenarios is not yet fully understood [133]. Because of this context, the next logical step in the IDE framework was the use of assigned routes to vehicles and pedestrians in order to obtain trips for cyclists.

OD estimation for vehicles is well established, with a broad range of count-based methods from entropy maximisation and bilevel programming to statistical inference and machine learning approaches, many of which rely on a prior OD matrix. In contrast, OD estimation for cyclists and pedestrians is less mature and depends on heterogeneous, mode-specific data such as bike-sharing records, tracking applications, camera counts, video recordings or wireless detection, each with its own coverage and sampling limitations. Existing multi-modal studies mostly derive demand through mode splits and assign each mode separately, or rely on intermodal networks and simulation-based approaches, but rarely adjust the demand of all road users jointly against observations. This leaves a gap for a framework that starts from a common prior generated from a synthetic population and adjusts it per mode using the data actually available for that mode. The IDE framework presented in Section 4 is proposed to address this gap.

3. Empirical Basis for the IDE Framework: Data Collection

This section describes the empirical data we collected, which serves as the empirical foundation for the IDE framework and is intended to help gain a better understanding of transportation patterns within the study area. While data is readily available for motorised vehicles, it is significantly more limited for bicycles and pedestrians. Bicycles and pedestrians require a level of detail that traditional sensors, like road loops, cannot provide. To address this limitation, we monitored traffic using high-resolution cameras. This approach revealed the true complexity of urban demand, and demonstrated that we could not rely on traditional datasets; without these video data, a significant number of pedestrians and cyclists would remain invisible to the model.

3.1 Traffic Survey Overview and Pilot Area

We conducted a traffic survey to analyse the traffic characteristics of highly complex urban intersections in Prague 6, Czech Republic, observing the traffic counts for both motorised and non-motorised modes. This area was selected for its diverse traffic environment, which includes significant interactions between motorised vehicles and vulnerable road users (VRUs). The traffic survey was located mostly in Dejvice, which is a major transit and educational hub that features metro stations, tram and bus stops, and university buildings. Several cameras were positioned along Evropská Street, a critical road that connects the city center to the Václav Havel Airport Prague.

The survey was conducted on September 19, 2024, for a duration of 12 hours (06:00–18:00). Tab. I summarises the distribution of tracked objects over this

Camera	Private Motorised Transport			Public Transport		Active Transport	
	Car	Van	Motorcycle	Bus	Tram	Pedestrian	Bicycle
C01	21,795	2,438	673	431	337	3,583	242
C02	30,431	3,057	765	982	279	1,647	154
C03	31,591	2,396	725	1002	361	476	83
C04	26,624	2,381	564	934	258	3,200	274
C05	24,899	2,712	440	1,423	283	2,298	178
C06	5,601	629	234	252	0	3,573	330
C07	4,220	626	114	51	0	10,558	187
C08	3	2	0	241	0	12,811	111
C09	15,390	1,580	770	952	545	26,502	75
C10	15,690	1,985	956	673	703	13,000	72
Total	**176,244**	**17,806**	**5,241**	**6,941**	**2,766**	**77,648**	**1,706**

Tab. I *Traffic counts across ten monitoring sites during the 12-hour traffic survey.*

observation period. A total of 10 camera locations (see Fig. 3) were established on existing street light infrastructure to collect high-resolution video data where traditional sensor availability for non-motorised modes is poor. The monitoring points were divided into two categories to capture specific modal movements:

- Preferred Cycling Corridors (Cameras 01–06): These sites were selected to capture bicycle movement, with locations determined by analysing link popularity to identify the most utilised paths. As shown in Fig. 3, the pink lines represent established cycling routes. The map confirms that cyclists frequently bypass the high-traffic main road at Vítězné náměstí in favor of the parallel roads covered by these cameras, ensuring the framework is informed by actual cyclist behaviour.
- High-Density Pedestrian Areas (Cameras 07–10): These locations focus on heavy foot traffic. As indicated by the green line marking Prague Metro Line A, these cameras are positioned near major public transport hubs, including metro exits, tram stops, and bus stations. Furthermore, the proximity



Fig. 3 *Overview map of selected camera locations in Prague 6 (Source: mapy.com).*

to university buildings and dormitories, indicated by the map markers near cameras 07–10, ensures the survey captures primary pedestrian paths. These high-occupancy facilities confirm the necessity of these specific monitoring points for establishing a reliable empirical baseline of pedestrian demand.

3.2 Empirical Identification of Multi-Modal Observability Gaps

The Prague traffic survey is used in this study primarily as an empirical diagnostic rather than as a validation of the proposed IDE framework. The survey was conducted to identify observability gaps across transport modes and to examine where conventional traffic data fail to represent pedestrian and cyclist movements adequately. The empirical findings were then used to inform the structure of the IDE framework, including its emphasis on heterogeneous data sources and mode-specific calibration. A numerical validation of the resulting OD estimation methodology is outside the scope of the present study.

The traffic survey was conducted using 10 cameras to capture video footage across the study area. Following that, raw recordings were processed using the DataFromSky (DFS) traffic analysis software [104]. The DFS TrafficSurvey Viewer was used to obtain multi-modal traffic counts for each monitoring site and to visualise the results (see Fig. 4).

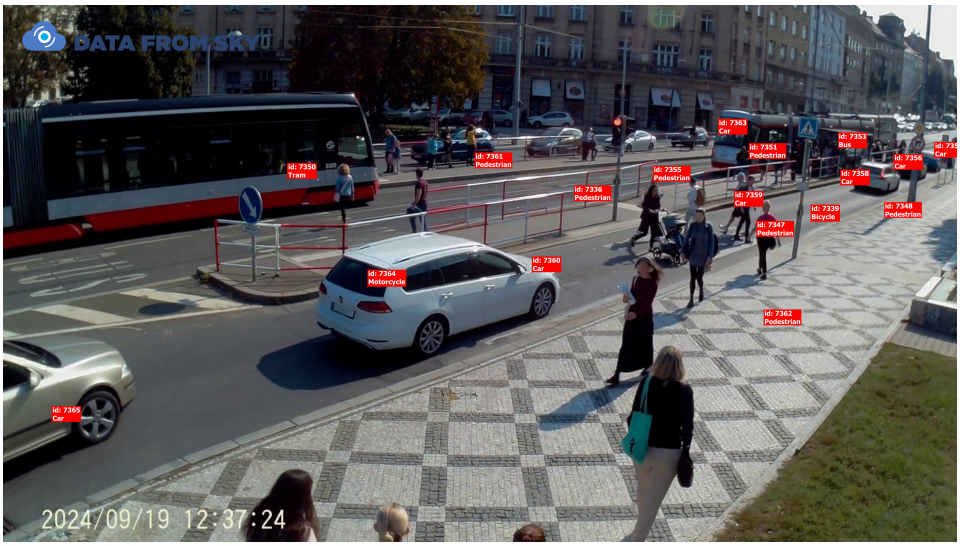


Fig. 4 *Traffic monitoring at Vítězné náměstí, Prague 6, as captured by Camera 09 and displayed in the DFS Viewer [104].*

The extracted statistics, summarised in Tab. I, provide the necessary empirical foundation for the IDE framework. This monitoring data reveals significant modal diversity across the Dejvice pilot area, with vulnerable road users (VRUs) accounting for a significant portion of total movement. Specifically, pedestrians and cyclists

combined (79,354 observations) represent roughly 40% of the volume seen in the private motorised transport (199,291 observations). The high volume of pedestrians identified at transit-adjacent sites (e.g., Camera 09) and the cyclist volumes at preferred corridors (e.g., Camera 06) justify the mode-specific adjustment, which is detailed in the IDE framework. This high proportion of non-motorised demand underscores the necessity of integrating VRU data to capture the true complexity of urban travel within the estimation framework.

The data in Tab. I highlights the critical importance of multi-modal monitoring in complex urban environments. Clarifying characteristics of the monitoring sites explains why the motorised traffic at Camera 08 is nearly non-existent, with only three cars, two vans, and zero motorcycles recorded, compared to a high pedestrian volume of 12,811. This occurs because the camera's area of interest was strategically focused on a metro exit and a primary walking path mostly used by students commuting to university buildings, rather than the roadway. Additionally, the zero values recorded for trams at Cameras 06, 07, and 08 indicate the tram tracks were not visible within the specific field of view of these cameras.

Furthermore, we observed that at certain locations, there is a significant imbalance in modal distribution which leads to limited observability for specific transport modes. For instance, at high-capacity motorised links such as Cameras 09 and 10, the recorded cyclist volumes are low, 75 and 72 observations, respectively, compared to over 15,000 cars at each site. These results confirm that relying on a single data source is insufficient for a comprehensive urban picture; therefore, the IDE framework proposes merging different data sources rather than using only one. Such insights provide the necessary empirical foundation for the framework, as traditional road-only sensors would completely fail to capture these critical VRU movements and localised travel demands.

While the video survey provided high-quality data, several technical and environmental constraints were noted. Large vehicles, particularly trams, occasionally blocked the view of pedestrians and cyclists for a few seconds. To minimise this, we mounted cameras at the highest available points. Since the cameras were not equipped with infrared (IR) sensors, recording was limited to daylight hours (06:00–18:00). We also postponed recording dates to avoid heavy rain or low visibility, ensuring we captured a "normal" day for cyclists and pedestrians. These limitations highlight why relying on a single data source is insufficient and justify the multi-modal integration used in the IDE framework.

These empirical findings informed the structure of the IDE framework. The observed spatial heterogeneity of modal flows, the limited observability of cyclists and pedestrians using traditional sensors, and the strong coupling between pedestrian, cyclist, and vehicular movements motivated (i) the use of synthetic populations to generate a complete prior OD structure, and (ii) the mode-specific calibration pipeline described in Section 4.

4. IDE Framework for Multimodal OD Estimation

This section presents the Integrated Demand Estimation (IDE) framework for multi-modal offline dynamic OD estimation. It begins with the conceptual structure and scope of the framework, then describes the four steps of the IDE framework in detail: synthetic population and prior demand generation, followed by pedestrian, vehicle, and cyclist demand estimation.

4.1 Conceptual Structure and Scope of the IDE Framework

The IDE framework, depicted in Fig. 5, consists of four sequential steps for estimating mode-specific OD demand. The conceptual framework follows a sequential four-step process. First, census, travel survey, land-use, building-registry, and OpenStreetMap data are used to generate a synthetic population and corresponding prior OD matrices for pedestrians, vehicles, and cyclists. Second, the pedestrian OD matrix is adjusted using GTFS information and pedestrian observations. Third, the vehicle OD matrix is adjusted using traffic counts and travel times. Finally, the cycling OD matrix is adjusted using bicycle counts, link popularity, and terrain information. In each mode-specific step, the prior OD matrix provides the starting demand, while the available observations and route-choice factors are proposed to constrain the resulting OD estimation. By combining synthetic population-based prior demand with mode-specific observations, the framework is intended to capture the distinct travel behaviour of each road user group.

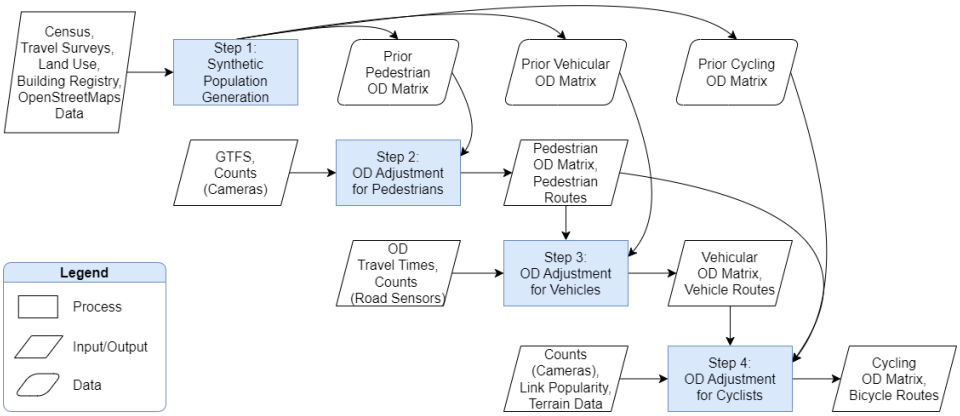


Fig. 5 *The IDE framework: travel demand estimation for vehicles, cyclists, and pedestrians. Reproduced from [138].*

Tab. II summarises the data inputs used in the IDE framework, their purpose, and their intended use in the OD estimation. All uses are part of the proposed conceptual design.

Data input	Purpose	Intended use in OD estimation
Census, travel survey, land use, building registry, OpenStreetMap	Generate prior demand for all modes	Synthetic population and prior OD matrices
GTFS	Identify PT access/egress locations and timing of PT-related trips	Pedestrian OD adjustment
Camera counts	Observe pedestrian and cyclist flows on selected links	Pedestrian and cyclist OD adjustment
Road sensor counts	Observe vehicle flows on selected links	Vehicle OD adjustment
Travel times	Observe vehicle travel times	Vehicle OD adjustment
Link popularity	Identify frequently used cycling routes	Cyclist OD adjustment
Terrain data	Represent elevation-related cycling effort	Cyclist OD adjustment

Tab. II *Data inputs in the IDE framework: purpose and intended use in OD estimation.*

4.2 Generating Synthetic Population

The first step utilises the framework proposed by [99]. Fig. 6 describes the processes and data flows of the applied framework. In summary, the methodology aims at sampling a population that matches census data (CD) with a Household Travel Survey (HTS) and assigns the population to facilities (i.e. buildings and open-air locations). This assignment would consider the activities people do at each facility and the capacity of visitors and inhabitants in addition to the characteristics of travel for each cohort of people within the HTS. Overall, the generated synthetic population would align the demographic and socioeconomic attributes of simulated individuals with real-world data. Additionally, the geographical distribution of the population would provide a realistic representation of activity patterns.

4.3 Estimating Pedestrian Demand

In the second step, the initial pedestrian OD matrix generated during synthetic population creation would be adjusted using General Transit Feed Specification (GTFS) data and pedestrian counts. GTFS data provides information about public transport (PT) schedules, including routes and stops. Camera recordings would be provide observed pedestrian flows on selected links of the network. For public-transport-related pedestrian trips, GTFS stop locations and timetable information would be used to define plausible access and egress locations and their temporal context. Walking-only trips would be assigned to the pedestrian network using an appropriate route-choice criterion. The resulting modelled pedestrian link flows would then be compared with camera-based pedestrian counts. The pedestrian OD matrix would be iteratively adjusted to reduce the differences between modelled and observed link flows, while GTFS information would provide additional spatial

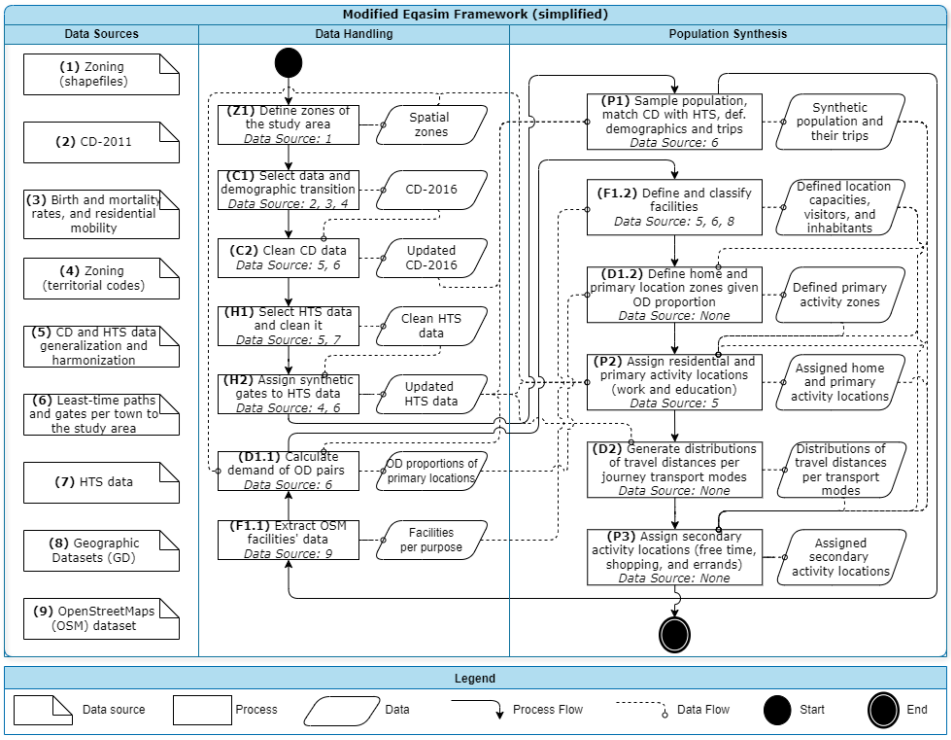


Fig. 6 *Data and process flowchart of the synthesis pipeline. Reproduced from [99].*

and temporal constraints for PT-related pedestrian trips. This integration is intended to produce an OD matrix that better reflects observed pedestrian movement patterns.

4.4 Estimating Vehicle Demand

The third step focuses on vehicle OD estimation, proposing the use of traffic counts, signal timings, and travel times based on vehicle speeds (from Google Maps API). As step 1 already provides an initial vehicular OD matrix, it would only need to be calibrated considering the least-travel time path and its adherence to real travel times per route and the calculated and measured observations (e.g. traffic counts). This step proposes using a traffic simulator that models vehicles and pedestrians and calculates average travel times. Once travel times and optimal routes are known, an optimisation would be run to minimise the differences between calculated and measured observations by variations of OD demands. This iterative calibration process would ensure that the adjusted OD matrix closely matches observed traffic patterns and real-world travel times, improving the accuracy of vehicle demand estimates, producing a more realistic representation of vehicular flows across the network.

4.5 Estimating Cyclist Demand

The fourth step focuses on estimating cyclist demand by integrating multiple data sources. The proposed approach would use bicycle counts, link popularity, and terrain data to inform this process. Bicycle counts would provide observed cyclist flows on selected network links and would be used to constrain the cycling OD estimation. Link popularity would reveal the most frequently used routes by cyclists, allowing the OD matrix to be adjusted more accurately based on observed travel patterns. Terrain data provides information on road elevation, which is a significant factor influencing cyclists' route choices and overall demand. Using these inputs, routes for bicycle trips would be assigned and the cycling OD matrix adjusted according to the "least discomfort" route, taking into account both elevation and observed bicycle counts. The calculated bicycle flows would then be compared with the observed counts, and the OD matrix would be iteratively adjusted to reduce the differences between them. This would ensure that the final OD matrix for cyclists reflects real-world cycling patterns and the influence of route attractiveness and physical effort on cyclist demand across the network.

5. Discussion

This section discusses our review and lessons learned in creating the IDE framework.

5.1 Review Highlights

The integration of different road users into a unified framework within a digital twin requires further research as pointed out by [124]. Since a digital twin network is composed of different functions and models for several subsystems (e.g. vehicle, pedestrian, and bicycle domains), a framework must be flexible enough to combine models for different stages and scenarios [125]. Multi-modal travel demand can affect both the overall performance of the transportation system and the costs for individual users [101]. Comparing multimodal travel demand can assist in determining which zones and OD pairs should be given priority [54].

Urban travel demand models typically take into account four transport modes: walking, cycling, public transport, and car [47]. The four-step model, usually used for simulating vehicle mode share and flows, is not typically employed for bicycles due to its design around oversized zone sizes and a simplified network, in addition to the high cost of use [25]. Integrating non-motorised modes into traditional transportation models is challenging in estimating intrazonal impedances for demand calculation [94]. Non-motorised trips tend to be short and often end up in the same traffic-analysis zone, making it difficult to model intrazonal trips accurately within macroscopic models due to spatial aggregation issues [94]. Yet, there is potential in alternative techniques to effectively model active travel modes such as cycling and walking.

Alternative methods include using aggregate statistics or spatial network analysis [25]. Spatial network analysis is a promising alternative to traditional transport models for modelling active travel [32]. It accounts for factors influencing walking

and cycling behaviour, such as distance, angular distance, motor vehicle traffic, and slope, leading to better understanding of route choice [32]. In addition to this, incorporating temporal information into direct-demand models can improve the accounting for alternative modes such as cycling and walking by estimating hazard exposure based on time of day [73].

Household based disaggregate models have been proposed to deal with the difficulties of regression techniques including independence and continuity among the variables [98]. In trip generation, the household is considered as the main unit and journeys depend on household characteristics [98]. Synthetic populations of individuals and households can be generated from census data to obtain more representative estimates in small areas without large-scale household surveys [89]. The disaggregated information shows individual behaviours more realistically than the zonal aggregated information, however, the disadvantage is that the distributions could be different in the future planing [98].

5.2 Lessons Learned from the IDE Framework

When developing a framework for travel demand modelling, it is important to consider both traditional and alternative approaches in order to capture the unique sensitivities and relative importance of each method and to accurately analyse the behaviour of different transport modes. A unified framework within a multimodal transportation system, including mode choice, is key to accurately capturing travel demand [69]. The IDE framework considers three transport modes (pedestrians, cyclists, and vehicles) and their mutual influence within the travel demand model.

The integration of multiple transport modes within the IDE framework was empirically motivated by the traffic survey conducted across ten locations in Prague 6. The observed spatial concentration of pedestrian demand at transit interfaces and the localisation of cyclist flows along preferred corridors revealed systematic observability gaps in motorised-only datasets. These findings suggest that relying on single-mode traffic data leads to structurally incomplete demand representations, particularly for vulnerable road users. The framework therefore aims to capture each mode's behaviour by considering the most important variables that affect the decisions of road users. Consequently, the IDE framework adopts a mode-specific calibration strategy that explicitly accounts for behaviours and interactions that remain invisible in traditional demand models, addressing the differences between traditional and alternative approaches within a single unified framework.

6. Conclusion

This paper conducted a non-systematic review of studies that have estimated ODs and discussed the strengths and limitations of the modelling approaches. Building upon this literature review and the empirical findings of a traffic survey, we proposed the IDE framework for OD estimation for vehicles, bicycles, and pedestrians. The framework addresses a central limitation of current origin–destination estimation practice: the fragmented treatment of motorised and non-motorised travel demand despite their strong interactions in urban environments. By synthesising existing OD estimation approaches with empirical evidence from a multi-modal

traffic survey, the IDE framework provides a unified methodological architecture for offline dynamic multi-modal OD estimation. The IDE framework takes into consideration the factors that influence travel demand for each travel mode, as well as data that can be used to estimate travel demand between an OD pair, including traditional traffic counts and socio-economic characteristics, together with less commonly used data such as travel times, road topography, link popularity, and public transport data.

Various methods can estimate the OD matrix from counting data, but the quality of the results depends on the transport network's characteristics [110]. Additionally, [50] acknowledged that traditional OD surveys are still essential for capturing land use and mode choice changes. To make the estimation of OD matrices easier and more cost-effective, collecting traffic counts at strategic urban road network locations over multiple years may be useful. The traffic survey results confirmed that strategic multi-modal monitoring can capture localised travel patterns, such as high-density pedestrian flows at transit hubs, that are critical for calibrating integrated demand models. However, in the absence of traditional OD surveys, surveys related to travel behaviour can be convenient when combined with census data and geographical databases to estimate OD matrices.

By reviewing the literature and presenting the IDE framework, this paper emphasises methodological innovation, providing a clear roadmap for future researchers. Rather than introducing a new estimation algorithm, the IDE framework provides a structured way to combine agent-based demand generation with trip-based OD adjustment using heterogeneous data sources. The goal was to ensure a thorough analysis illustrating the potential generalizability and adaptability of the IDE framework to be tested in future work. While the traffic survey highlighted constraints like technical and environmental limits, these challenges emphasised the necessity of the IDE framework's multi-source data integration as a solution for maintaining continuous observability. Recognising these factors alongside practical constraints such as resource availability, the IDE framework nevertheless provides a meaningful contribution to demand modelling, serving as a methodological baseline for urban digital twins, where consistency across transport modes is a prerequisite for meaningful policy analysis and operational decision support.

The present study focuses on offline dynamic OD estimation and does not attempt a full numerical validation, which is left for future work. Future research should focus on (1) the construction of the multi-modal transport and network model in a traffic simulator, (2) the application of the synthetic population generation framework proposed by [99], and (3) an optimisation model for minimising the differences between calculated and measured observations. The output of the optimisation model must provide calibrated OD matrices derived from the initial synthetic population OD matrices. A test with synthetic data would be an appropriate way to evaluate and validate the performance of our methodology, since model parameters and OD demand are not directly observable [6]. The framework should then be implemented in a real urban area using observed traffic, pedestrian, and bicycle counts. Expected challenges include incomplete spatial coverage of observations, differences in the time intervals of the data sources, and uncertainty in pedestrian and cyclist route choice, which is harder to observe than vehicle route choice. Once calibrated, the resulting multi-modal OD matrices could be

integrated into urban digital-twin platforms to support traffic simulation, scenario testing, infrastructure planning, and operational decision support. Regarding modelling and evaluation of synthetic testbeds: refer to [30] for traffic simulation model parameters calibration, and [79] for OD flow estimation.

Author contributions

Halil Çevik: Conceptualization, methodology, formal analysis, writing – original draft, writing – review & editing, visualization. André Maia Pereira: Conceptualization, methodology, writing – original draft, visualization. Ondřej Přibyl: Writing – review & editing, supervision.

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