



REVIEW DIFFERENT METHODS FOR ESTIMATING THE ORIGIN-DESTINATION MATRIX

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ABSTRACT

In transportation planning and engineering projects, the process of calculating and estimating the origin-destination (O-D) matrix is very important, to understand how travel demand occurs within an urban area. In this review, some of the main methods and techniques used in origin-destination matrix estimation are summarized and explained, highlighting some of their objectives, applications, results, and sometimes their limitations. It should be noted that in each method of origin-destination matrix estimation, there are challenges, including issues related to the accuracy of data collection and complex calculations, as well as issues related to local standards. In short, it can be said that the process of origin-destination matrix estimation depends on the accuracy and availability of data. In the future, data collection techniques are expected to develop further and improve the accuracy of data collection, which is an important issue in the process of origin-destination matrix estimation.

KEYWORDS

Origin-destination matrix, Gravity model, Extended Kalman Filtering (EKF) algorithm, Bayesian approach, Fratar method, ITS.



1. INTRODUCTION

Origin-destination matrix (O-D) can be defined as a number that indicates the daily movement and trips that individuals make between different places, for example from home to work, and is an important input in various fields such as transportation planning, economics, and environmental science. The (O-D) matrix in transportation represents the flow that occurs between pairs of areas (origin and destination) within the area of interest and is defined for study (Rong et al., 2024). It is worth noting that different cities often face severe traffic congestion, which causes a lot of time and money to be wasted, and this is considered a loss that must be reduced (Mohammed and Yousif, 2020). Most traffic problems are directly related to traffic safety issues, as increased traffic flow can lead to an increase in the number of accidents on road networks, especially at the most dangerous locations on these networks: intersections (Khudhair et al., 2025). On the other hand, one of the most important reasons for the failure of road networks, whether highways or urban roads, is the lack of periodic maintenance or failure to implement them (Abbas, 2024). Therefore, the process of supporting and developing the transportation sector is based on approximately three main tasks, which are (1) shortening travel times during transportation, (2) reducing and limiting accidents, and (3) enhancing and developing freight transportation (Asad and Saeed, 2024). Hence, we find that the weaknesses of many city streets, including congestion, as well as poor operation and traffic control, are linked to the development of these networks. Future planning, including density control and land use planning, can limit and mitigate the causes of traffic congestion and also lead to improved and developed transportation systems (Alkaissi, 2024). Therefore, in transportation planning, the (O-D) matrix is calculated, which is an effective and essential element in making improvements by the authorities and administrative centers concerned with the various transportation networks. It is worth noting that these improvements are not for daily trips, but rather to know the investments and infrastructure required for transportation and to know the expected needs in the future (Galabrese et al., 2011). Estimating the (O-D) matrix in transportation planning is an important process in assessing and analyzing transportation characteristics. However, due to the large number of surveys and direct interviews involved in collecting origin-destination data, the process of estimating the (O-D) matrix is often expensive and sometimes difficult. Many automated data collection systems have emerged in addition to modern communication systems. Therefore, it is now possible to generate and collect large data with very high accuracy instead of the previously used methods that relied on small spatial surveys and low accuracy. Modern (O-D) data is an important source that helps planners understand and know travel and transportation patterns (Abrahamsson, 1998) (Mohammed and

Oke, 2023). In transportation engineering and planning, the transportation demand forecasting model consists of four stages, and the transportation demand matrix estimate is obtained in the second stage (Dragu and Roman, 2019). The (O-D) matrix refers to two aspects: 1-Numeric values representing the number of trips for each cell of the (O-D) matrix. 2- Structuring and organizing the process of distributing trips that take place within different transportation zones, thus clarifying the shape and structure of the matrix (Afandizadeh et al., 2021). The (O-D) matrix has many applications in transportation planning as it focuses more on the characteristics and activities of traffic between the origin/destination area and due to the great advancement and development of software technology the task of collecting data for various transportation activities has become extensive (Dong, 2021). Previously, the methods for collecting (O-D) matrix data consisted of only specific methods, namely the direct method and the indirect method, but big data has been included and used as one of the (O-D matrix) estimation methods. Fig.1 shows the various methods by which the origin and destination matrix can be estimated (Tamin and Fadilah, 2021).

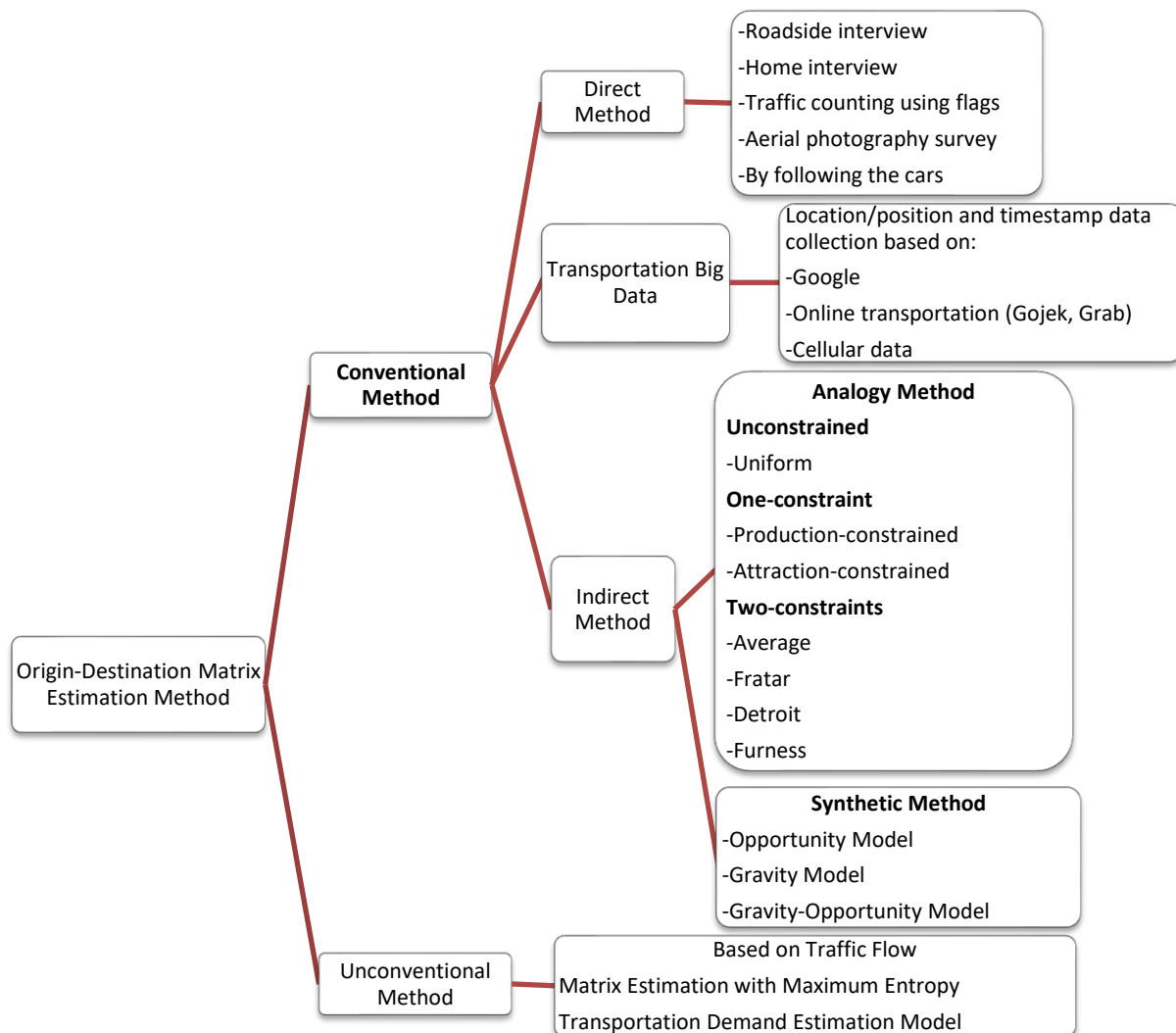


Fig. 1 Origin-Destination Matrix (O-D) estimation methods (Tamin and Fadilah, 2021).

2. BACKGROUND ON PREVIOUS STUDIES

Estimating and extracting the (O-D) matrix of a specific road and transportation network effectively is a fundamental and required issue in the field of transportation because it enables those interested and practitioners in the transportation planning process to better manage and know the requirements of these networks, in addition to enabling researchers to apply many mechanisms, methodologies and monitoring techniques to test and know the validity of these methods (Englezou et al., 2024). Therefore, during the past few years, many studies have been conducted through which techniques, methods; approaches, and modeling processes can be developed to estimate the (O-D) matrix. Table 1 shows these studies, indicates the most important techniques used in them, and provides an overview of them.

Table 1. Summary of the most important studies on the estimation of the (O-D) matrix

Reference	The Study Objective	Methodology	Key findings
Hualan et al., 2020	Suggest a method for producing an (O-D) matrix with reasonable ratios, fewer variables, less complexity, and lower cost.	Estimation of the flow of both the on/off ramp of the expressway.	The distance a driver travels when moving from one ramp to another is half (1/2) of the total length of the freeway.
TSENG et al., 2013	Provide a model for estimating the dynamic (O-D) matrix.	Traffic flow estimation, adoption of a model consisting of (GHSOM), (GP), and use of a composite algorithm between (CTM) and (EKF).	The results showed the efficiency of the proposed model.
Afandizadeh et al., 2021	Develop a model that uses (ML) techniques and data from (ITS).	Five application models (CNN, Light GBM, RF, MLP, KNN) and MISSIM are used.	The results showed that the (CNN) model is efficient and has the lowest error in terms of RMSE and MAPE.
Xiong et al., 2023	Propose a reliable and integrated method that uses deep learning methods and techniques to generate (O-D) sequences.	SYMO software was used to simulate the network.	The proposed method for searching is superior to the traditional optimization method.
Kashkhah et al., 2022	Design and develop a real-time system and use web patterns to perform analysis.	Two types of data were used to construct the (O-D) matrix, namely static data and dynamic data obtained from sensors.	The algorithms used during the study showed encouraging results, and in terms of sensor data, they showed a balance between performance and quality.

Reference	The Study Objective	Methodology	Key findings
Galliani et al., 2024	Develop and deliver an innovative pipeline that can integrate subscription and ticket sales data using APC.	Application of gravity model to estimate and handle missing data within (O-D) matrix, which is improved using IPF algorithm.	The proposed approach can balance and bridge the gap between data availability and the ability to estimate an accurate O-D matrix.
Lin and Chang, 2005	Developing a model to estimate the (O-D) matrix. The proposed model is characterized by reducing the variance in travel times.	To implement this model and ensure its usability within a large network, a device was built and AIMSUN 4.0 software was used for simulation.	The results show that the model allows good and reasonable results for estimating the dynamic (O-D) matrix.
Kwon and Variya, 2005	Develop an algorithm that includes a statistical model to estimate the (O-D) matrix from data related to vehicle trajectories obtained using techniques such as (AVI).	The algorithm involves developing and improving a method for finding the initial standard error of an (O-D) matrix.	The result was that the proposed algorithm performed well.
Barcelo et al., 2012	Attention is drawn to the ATIS/ATMS requirement to estimate the time-based (O-D) matrix by estimating traffic flow variables.	This paper presents a Kalman filtering (KF) approach that deals with traffic flow data available from Bluetooth sensors.	The computational results show that the proposed approach provides good estimates and values in traffic simulation tests.
Van den Berg et al., 2007	Development of a model to simulate traffic flows within dual urban networks (urban roads and freeways).	For the freeway part of the network the METANET model was used, and for the urban road part of the network Kashani's model was used.	The results showed the possibility and efficiency of applying the proposed approach.
Chiou et al., 2011	Propose a mathematical model to identify LPR plates and minimize errors in the (O-D) matrix.	A genetic algorithm is proposed to validate the model.	The results of the study included identifying the best places to identify license plates.
Yuanqing et al., 2010	Propose a method to improve the accuracy and reliability of (O-D) matrix estimation.	The initial (O-D) matrix was calculated using the Frater and Gravity method, and the (O-D) matrix was estimated using TransCAD software.	The result showed that this method can achieve accurate results at a lower cost by collecting traffic flow data.
Abdullah and Asmael, 2024	Evaluation and knowledge of the level of the road network transportation system.	Several programs were used, including ArcGIS to build the road network, in addition to TransCAD, which was used to analyze the network.	The results obtained are among the most important information through which we can know the possibilities that can be used to improve the network of the study area.

Reference	The Study Objective	Methodology	Key findings
Muthuswamy et al., 2003	Introducing an offline approach to estimate the static (O-D) matrix as well as to minimize potential deviations between the actual and predicted number of slopes.	Five different methods were applied to find the initial values of the boundaries and the minimization problem, the traffic flow was simulated using AIMSUN and MINOS, and FORTRAN77 was used.	Results The potential and superiority of the proposed approach are due to its simplicity.
Huo et al., 2023	To present an algorithm and reach solutions to many problems and challenges facing the process of dynamic (O-D) matrix estimation.	In this paper, (17) alternative-based optimizations are proposed, including the Bayesian optimization algorithm.	As for the proposed approach, the results indicated its validity and superiority.
Barcelo et al., 2010	Verifying the quality and efficiency of data obtained via Bluetooth sensors for mobile devices.	The dynamic (O-D) matrix is estimated based on travel time. The paper also tests and develops the KF approach.	The results showed that the proposed model provides good results for non-congested periods.
Alkawaz and Asmael, 2018	Estimating the (O-D) matrix based on traffic data instead of using the traditional method which requires effort and a large amount of data.	Based on traffic data of the road network, a cost-effective method, the Nielsen method, was used using TransCAD software.	The results obtained are considered good and through them, several solutions were presented to improve the network transmission field.
Fernández et al., 2020	Improving the transportation capacities of different goods within urban areas and networks by calculating the (O-D) matrix using the entropy maximization approach, which is more effective and convenient than different gravity approaches.	The proposed model is applied to a real road network case and the mathematical approach is implemented using Ampl and CPLEX12-9 solver.	The presented model is found to be efficient and good for obtaining computational values in low time and with almost negligible approximation error.
Ait-Ali and Eliasson, 2022	Study the impact and importance of data that can be added to the results of the (O-D) matrix.	Data were collected on station arrival rates, connection flows and average trip distance, and peak hour data were collected for three times: morning, afternoon and midday.	The results show that data on station arrival rates can improve the calculation of the (O-D) matrix, and for link flows, it is also possible to improve the estimation and calculation of the matrix.
WAMBRA UW et al., 2017	Estimating and calculating the distribution of trips using one of the traditional methods.	Data were collected through home interviews and (O-D) trip surveys. During this study, an indirect method, the Fratar method, was applied.	The Frater method has given acceptable and good results.

Reference	The Study Objective	Methodology	Key findings
Ekowicaksono et al., 2016	Estimation of the O-D matrix for Bogor City, which has an estimated population of about one million people.	The gravity model and the morning travel time of workers were used to form the (O-D) matrix and during this study, the calibration process was carried out using (Heyman method).	The result was that the value of $\beta = 1.1679 \times 10^{-7}$, which can be adopted and applied in other studies in the future.
JIAO and LU, 2005	Propose a model that can optimize and process the Internet traffic count data obtained from ITS systems to estimate the dynamic (O-D) matrix.	Implementation of nonlinear and dynamic relationships. Two sets of recurrent models are included as well as the corresponding genetic algorithm.	The results showed the efficiency of the proposed algorithms and models.
Montero et al., 2015	A framework is proposed to estimate the dynamic (O-D) matrix based on counting and travel time data collected from smartphones and Bluetooth sensors.	The KF model is applied and a special formula of the KF model is developed that can deal with congestion problems, in addition to implementing the proposed model through MATLAB KFX3T.	The results suggest that experimental evidence involving a medium-sized network study is needed.

3. COMPARISON BETWEEN DATA COLLECTION OF O-D MATRIX METHODS

Estimating a source-destination (OD) matrix requires a comparative analysis of different data collection methods. Each method has strengths and weaknesses, making it suitable for different contexts based on the level of accuracy required and available resources. These methods include:

1. Roadside Surveys vs. Automated Data Collection
2. Traffic Count Methods vs. Probe Vehicle Data

Automated Data Collection and Probe Vehicle Data are crucial for large-scale studies and real-time traffic management, offering high granularity but posing challenges related to privacy and data processing. The choice of method depends on the objectives, the data available, the resources (time, budget, and computational power), and the required level of accuracy. Combining multiple methods often yields the best results, as it leverages the strengths of different approaches.

Criteria	Roadside Surveys	Automated Data Collection
<ul style="list-style-type: none"> • Data Collection • Accuracy • Cost • Temporal Coverage • Scalability • Data Types • Suitability 	<ul style="list-style-type: none"> • Manual involves interviewing drivers or collecting license plate data • High if conducted thoroughly; direct data on travel patterns • High (requires significant manpower) • Limited to the duration of the survey • Low; difficult to scale over large areas • Rich, includes trip purposes, demographics • Useful for small-scale studies with a budget for fieldwork 	<ul style="list-style-type: none"> • Automated and continuous, using sensors or cameras to count vehicles • Moderate to high; depending on sensor coverage and data processing • High initial cost but lower maintenance costs over time • Continuous, 24/7 data collection • High; can be deployed over large networks • Limited to traffic volumes and sometimes vehicle types • Suitable for large-scale, long-term data collection and monitoring

Fig. 2 Comparison between Roadside surveys and Automated Data collection.

Criteria	Traffic Count Methods	Probe Vehicle Data
<ul style="list-style-type: none"> • Data Collection • Accuracy • Granularity • Cost • Data Processing • Temporal Analysis • Suitability 	<ul style="list-style-type: none"> • Traffic volumes at specific locations • Limited; provides only aggregate flow data • Low; cannot capture detailed OD flows • Low to moderate (simple setup) • Simple; involves volume matching techniques • Limited; often requires manual segmentation • Good for initial OD estimation and simple models 	<ul style="list-style-type: none"> • Vehicle trajectories, travel times, and patterns • High; provides detailed, trip-level data • High; can capture individual vehicle movements and temporal dynamics • High; requires data purchasing or sensor network setup • Complex; requires data filtering and processing • Continuous; can analyze temporal variations in travel demand • Best for dynamic models and large-scale OD studies

Fig. 3 Comparison between Traffic Count Methods and Probe Vehicle Data.

4. COMPARISON BETWEEN METHODS FOR ESTIMATING AN ORIGIN-DESTINATION (OD) MATRIX

A comparative analysis of different methods for estimating the source-destination matrix. Each method has its advantages and disadvantages, including:

1. Static Models vs. Dynamic Models
2. Model-Based Approaches vs. Data-Driven Approaches
3. Survey-Based Methods vs. Machine Learning Approaches

Criteria	Static Models	Dynamic Models
• Approach	• Uses fixed travel patterns and average data	• Models traffic flow variations over time (e.g., peak vs. off-peak)
• Complexity	• Relatively simple; easy to implement	• High; requires sophisticated algorithms and real-time data
• Data Requirements	• Moderate; relies on historical data and traffic counts	• High; needs continuous data streams and real-time updates
• Accuracy	• Low to moderate (simple setup)	• High; better at modeling congestion and temporal traffic fluctuations
• Computational Effort	• Low; quick to run on most computers	• High; computationally intensive, especially for large networks
• Use Cases	• Suitable for planning studies and average conditions	• Useful for real-time traffic management and simulation studies

Fig. 4 Comparison between Static Models and Dynamic Models.

Criteria	Model-Based Approaches	Data-Driven Approaches
<ul style="list-style-type: none"> Methodology Assumptions Ease of Use Data Dependency Adaptability Application 	<ul style="list-style-type: none"> Relies on theoretical models and assumptions Requires assumptions about travel behavior (e.g., impedance) Relatively straightforward; well-documented methods Moderate; can use limited data sources Limited; not easily adaptable to sudden changes Transportation planning and policy analysis 	<ul style="list-style-type: none"> Uses data patterns and statistical/machine learning techniques Fewer assumptions; The model learns directly from the data Complex; requires expertise in data science and machine learning High; needs extensive and high-quality data for accurate modeling Highly adaptable; can update models with new data Real-time traffic systems, congestion prediction, adaptive routing

Fig. 5 Comparison between Model-Based Approaches and Data-Driven Approaches.

Criteria	Survey-Based Methods	Machine Learning Approaches
<ul style="list-style-type: none"> Data Sources Accuracy Data Collection Flexibility Cost Predictive Power Suitability 	<ul style="list-style-type: none"> Self-reported data from households or drivers High for reported trip purposes and patterns Time-consuming and expensive Limited; predefined questions and methods High (survey logistics and manpower) Limited to survey coverage and data collected Useful for a detailed understanding of travel behavior 	<ul style="list-style-type: none"> Large datasets (GPS, mobile phone data, historical traffic) High, if trained on sufficient and quality data Requires access to extensive, high-quality datasets Very flexible; models can adapt to various data inputs and patterns High initial cost for data and model development, but low operational cost High; can predict and model complex travel behaviors dynamically Best for big data analysis and dynamic traffic forecasting

Fig. 6 Comparison between Survey-based methods and Machine Learning methods.

Static mathematical models are typically used to estimate a constant O-D matrix, meaning that the distribution of trips between the origin and destination points is constant (the factors affecting the trip pattern and behavior do not change over time). These mathematical models include:

1. Gravity Model

$$T_{ij} = K * \frac{O_i D_j}{f(c_{ij})} \quad (1)$$

Where:

T_{ij} = Number of trips from origin (i) to destination (j).

O_i = Size (e.g., population or employment) of the origin zone (i).

D_j = Attractiveness (e.g., land use, employment) of the destination zone (j).

c_{ij} = Travel cost (distance, time, or monetary cost) between origin (i) and destination (j).

$f(c_{ij})$ = Function of travel cost (often $f(c_{ij}) = c_{ij}^\beta$, where β is a constant).

K = Calibration constant (determined through data fitting).

2. Fratar Method

$$\hat{T}_{ij} = T_{ij} * \frac{O_i}{\sum_j T_{ij}} * \frac{D_j}{\sum_i T_{ij}} \quad (2)$$

Where:

\hat{T}_{ij} = Updated number of trips from origin (i) to destination (j).

T_{ij} = Initial (base) number of trips from origin (i) to destination (j).

O_i = Total number of trips originating from origin (i).

D_j = Total number of trips destined for destination (j).

$\sum_j T_{ij}$ = Total trips departing from the origin (i) in the initial OD matrix (sum of all trips from (i) to all destinations (j)).

$\sum_i T_{ij}$ = Total trips arriving at destination (j) in the initial OD matrix (sum of all trips to (j) from all origins (i)).

Entropy Maximization Model

$$H = -\sum_{ij} T_{ij} * \log (T_{ij}) \quad (3)$$

Subject to:

$$\sum_j T_{ij} = O_i \quad \forall_i$$

$$\sum_i T_{ij} = D_j \quad \forall_j$$

Where:

H = Entropy (uncertainty) of the trip distribution.

T_{ij} = Number of trips from origin (i) to destination (j).

O_i = Total number of trips originating from origin (i).

D_j = Total number of trips destined for destination (j).

Dynamic mathematical models are used to estimate a dynamic (O-D) matrix. Dynamic conditions include factors and changes that occur over time, such as different traffic patterns, accidents, congestion, land use changes, and other dynamic factors that influence travel behavior. These models differ from static models in that they provide estimates that are more accurate and results. These models include:

Dynamic Traffic Assignment (DTA)

$$\frac{dF_{ij}(t)}{dt} = r_{ij}(t) * \left(1 - \frac{F_{ij}(t)}{C_{ij}}\right) \quad (4)$$

Where:

$F_{ij}(t)$ = Flow between origin (i) and destination (j) at time (t).

$r_{ij}(t)$ = Rate at which traffic is moving from (i) to (j).

C_{ij} = Capacity of the route between (i) and (j).

Bayesian Dynamic Model

$$p(T(t)D(t)) = \frac{p(D(t)T(t)) * p(T(t)T(t-1))}{p(D(t))} \quad (5)$$

Where:

$p(T(t)D(t))$ = the posterior distribution of the O-D matrix at time t.

$p(D(t)T(t))$ = the likelihood of the observed data (e.g., traffic counts) given the O-D matrix.

$p(T(t)T(t-1))$ = the transition probability, which models how the O-D matrix evolves.

$p(D(t))$ = the normalization constant.

Regarding survey-based methods, Asad and Hadi, in their 2024 study, which included a field survey, stated that participatory surveys can be classified, based on their method of administration, into four groups: phone-based surveys, in-person interviews, mail-out surveys, and web-based surveys. However, these methods may sometimes have both disadvantages and advantages that should be considered (Asad and Hadi, 2024). Therefore, it is worth noting that survey methods offer valuable insight into travel behavior. However, they are expensive and difficult to implement on a large scale, which is one of their drawbacks. Nevertheless, they are best suited for comprehensive studies that require detailed data on traveler characteristics. There are several types of surveys and interviews, some of which are outlined in Table 2.

Table 2. The most important types of survey-based methods

Survey Type	Data Collected	Advantages	Challenges
Household Travel Surveys	(O-D) trip purpose, mode	The data is detailed and comprehensive	Expensive and time-consuming method
Travel Diary Surveys	Detailed information for daily trips	Rich data, especially for Specific time periods	This method requires cooperation between researchers and respondents
Intercept Surveys	Trip information and details at specific locations	Real-time data collection	Limited to specific locations, biased sample
GPS-based Surveys	Origin-destination, Exact routes	The spatial accuracy is high	high cost of equipment
Smartcard-based Surveys	Entry and exit points, travel times	Real-time, accurate data	Limited to public transport data
Mobile Phone Surveys	GPS or cell tower data, trip routes	The data obtained is accurate and large-scale	Privacy concerns, data processing issues
Web-based Surveys	Data related to trip details are from online questionnaires	Reasonable cost and large sample size for large-scale surveys	Internet access problem

5. DISCUSSIONS

The estimation of the (O-D) matrix, whether static or dynamic, is of great importance in transportation engineering and planning, as well as in traffic management and making important decisions related to the planning of infrastructure for various transportation networks. The process of estimating the (O-D) matrix includes many important aspects and difficult challenges, some of which can be summarized as follows:

- Data collection is an important issue but is often difficult to obtain accurately and comprehensively for each (O-D) pair, as traditional surveys, GPS data, and traffic statistics may not cover all trips, resulting in incomplete and inaccurate data.
- The diversity of travel patterns and behavior is one of the main reasons why demand forecasting and data collection are difficult.
- Dealing with the dynamic nature of transportation is one of the most important requirements of (O-D) matrix estimation, as demand for trips can vary according to time, day, road conditions, and weather.
- The mathematical models used to estimate the (O-D) matrix are often complex, involving many statistical techniques, advanced optimization, and obtaining results from incomplete data. Therefore, the task of developing a model that can balance accuracy and complexity is a significant challenge.

- For large-scale transmission networks, the task of estimating the (O-D) matrix is usually difficult due to the large amount of data, and finding algorithms that can handle the huge amount of data is a significant challenge.

Addressing these and other challenges requires advanced and improved modeling techniques, as well as the ability to integrate different data collection methods and continuous validation that can enhance the accuracy of data collection.

6. CONCLUSIONS

(O-D) matrix estimation is a very important process and is the key factor for many urban planning applications, traffic flow, and knowing the most important measures for improving infrastructure because the (O-D) matrix helps in understanding different travel behaviors. By reviewing many research papers on (O-D) matrix estimation for urban networks, especially freeway networks, it was concluded that: The reliability and accuracy of (O-D) matrix estimation largely depends on the input data, the quality of that data, and the methods chosen which include traffic counting data, traffic flow, survey and the use of advanced modeling techniques. However, the limitations of the (O-D) matrix estimation process can pose a significant burden during this process, including non-automatic travel calculation and handling of unobserved trips. Future studies can work on integrating different data sources in real-time to develop prediction and modeling techniques.

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