KFI: A novel keyframe interpolation methodology for improving the efficiency of dynamic OD estimation on large urban networks.

R. Malhotra[a], C. Advani[a], P. Corry[b], D. A. Bhaskar[a,*]

[a] School of Civil and Environmental Engineering, QUT, Brisbane
raghav.malhotra@qut.edu.au, chintan.advani@gmail.com, ashish.bhaskar@qut.edu.au
[b] School of Mathematical Sciences, QUT, Brisbane
* Corresponding author

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# 1. INTRODUCTION

Traffic management systems help in data-driven decision-making, manage traffic demand, and provide valuable insights for planning long-term infrastructure projects and policies. Simulation systems (such as Aimsun Live) are a component of real-time traffic management systems that act like a digital twin for the transport network. These simulation systems are necessary for several applications, such as cost-effective performance evaluation of strategies, real-time traffic management, predicting traffic behaviour, evaluating infrastructure changes, etc. Time-dependent travel demand data is one of the crucial inputs to these systems, represented as dynamic origin-destination (OD) matrices.

These dynamic OD matrices (travel demand) are not directly observable and are generally estimated. In literature, several techniques for OD estimation exist, such as traditional approaches like travel demand surveys (Bierlaire and Toint, 1995, de Dios Ortúzar and Willumsen, 2011, Stopher and Greaves, 2007); statistical and optimisation techniques (Ashok and Ben-Akiva, 2002, Cascetta, 1984, Van Zuylen and Willumsen, 1980, Willumsen, 1978) and advanced machine-learning techniques (Krishnakumari et al., 2020, Ou et al., 2019) are proposed. Among these methodologies, the bi-level adjustment framework (Maher et al., 2001) has been a widely accepted technique for estimating OD flows, which aims to reduce the error between the estimated and observed traffic flows on the upper level and leveraging a traffic assignment estimation on the lower level to relate OD flows to link counts. While the applicability of this method is well established in the literature, a significant challenge in the form of computational cost leading to high temporal requirements remains intact.

Inspired by video summarization techniques, our research adapts similar principles to the domain of dynamic OD matrices. Analogous to summarizing video sequences into key shots, we aim to reduce the computational burden of estimating OD matrices by focusing on key intervals and interpolating the gaps between them. Our study introduces a novel framework that significantly cuts down computational time, making it applicable for real-time applications in Dynamic Traffic Management Systems as well as offline tools.

Key contributions of the paper include:

- Introducing a novel framework for OD matrix estimation, drastically reducing computation time for both real-time and offline scenarios.

- Justifying the assumption that travel demand evolves gradually, necessitating estimation only for a subset of time intervals (termed key intervals) to achieve accurate OD matrix estimation.
- Reduced OD estimation runtime allows for more iterations in bi-level OD adjustment, leading to improved convergence.
- Providing a detailed analysis of the new methodology's components and introducing a novel approach for identifying key intervals.
- Comparing the performance of our Keyframe Interpolation (KFI) approach against a state-of-the-art bi-level adjustment framework using a generalized least squares formulation.

# 2. Methodology

The prior OD matrices are an essential input to both the preprocessing step and a starting point for the estimation process, as shown in Figure *1*. The pre-processing task of data generation generates the database consisting of key intervals for a given type of day based on the prior OD matrices. Once this dataset is generated, it need not be generated again unless the prior OD matrices are updated. The terminology for this step is adopted from video summarisation, known as Shot Boundary Detection (SBD). This is followed by estimating the partial set of OD matrices (composed only of key intervals), incorporating link flows as the basis for adjustment.

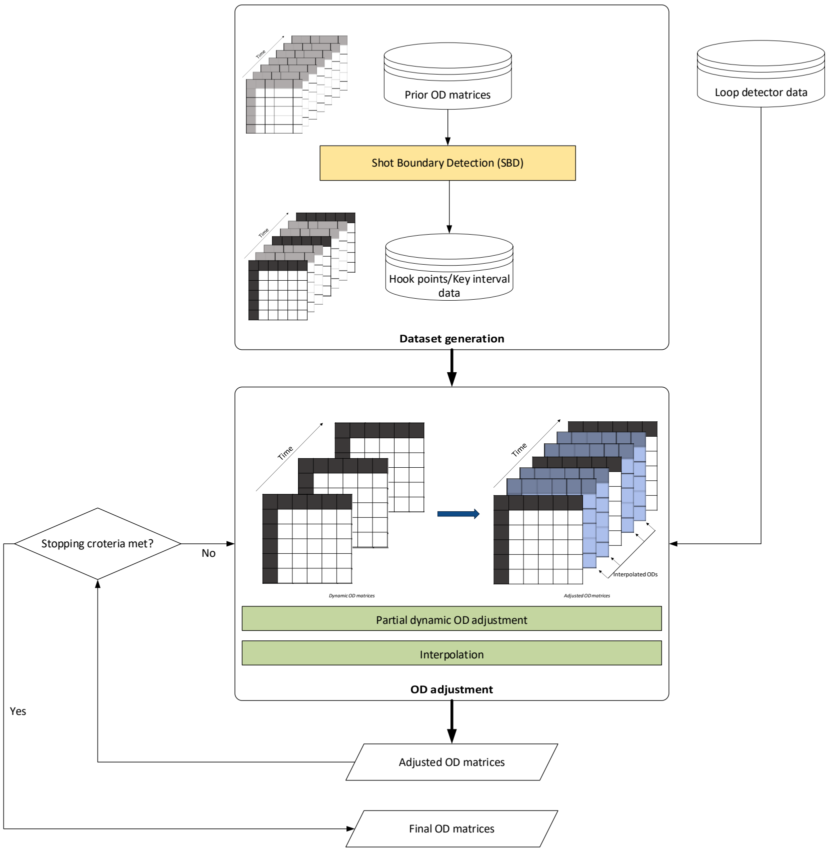



Figure 1: KFI framework.

Two main components are identified as critical to the quality of estimated OD matrices: *Shot Boundary Detection* and *Interpolation*. Therefore, these components play a crucial role in determining accurate estimations and are critical.

## 2.1 Shot Boundary Detection (SBD)

Shot Boundary Detection (SBD) identifies the key intervals by extracting the underlying information within the prior OD matrices. SBD is a pre-processing task that utilizes the prior OD matrices to determine which intervals in the period define the overall trends in the demand progression through the day.

SBD has been extensively studied in the video summarization domain (Zhang, 2006, Yuan et al., 2007, Smeaton et al., 2010). While some of the methodologies from this domain exploit contextual information within video frames (luminance, flash detection, etc.), others are more flexible in their application as they can be utilised for any generic time series (such as travel demand). Some of these methods include but are not limited to, Rule-based classifiers (threshold-based detection of keyframes), Statistical machine learning such as K-means clustering (a time continuity constraint is necessary for these algorithms), graph-based partitioning model (Yuan et al., 2005). These methods treat the SBD task for OD data like a video-based partitioning problem. One of the drawbacks of this is that the previous methodologies treat the OD matrices as complete structures while the interpolation process is performed independently for each cell of these matrices, i.e., for each OD pair. This leads to a disconnect between SBD and the next task in the KFI approach, interpolation. While interpolation and SBD are critical in determining the quality of the output ODs, these sub-components should complement each other and perform together. To address this, we propose a new algorithm for SBD based on individual demand, which considers the feedback from interpolation as an objective function.

### 2.2 Interpolation

The general idea behind interpolation is to use the known data points to create a function that can estimate values at any point within the range of the data. For KFI, once the key intervals are identified for an OD time series, interpolation is used to fill the missing gaps within the time series data. Several interpolation techniques exist in the literature, such as linear interpolation, polynomial interpolation, natural spline interpolation, monotonous spline interpolation, nearest neighbour interpolation, inverse distance weighting interpolation, etc. Given the nature of OD time series data, which shows progression through time in a systematic manner, we have explored the following interpolation techniques in this paper:

1. Linear interpolation
2. Natural spline interpolation
3. Monotonous spline interpolation

### 2.3 Split Simulations

Bi-level adjustment is a robust technique widely used in various OD estimation applications. One of the essential inputs in OD adjustment is the assignment matrix, which relates travel demand to link counts for each time interval in a dynamic scenario. The assignment matrix is obtained as an output from running traffic simulations using prior OD estimates. This process makes up the lower level of bi-level OD adjustment and is time-consuming.

The split simulation approach aims to reduce the time complexity of the lower level in bi-level OD adjustment by only capturing the assignment matrices for intervals that have been identified as key intervals. This leads to a minimal loss in accuracy while significantly reducing the time taken to run the simulations and estimate assignment matrices.

## 3. RESULTS

As proof of the concept the research is applied on the city of Logan, Queensland, Australia, with 230 centroids as shown in Figure 2.

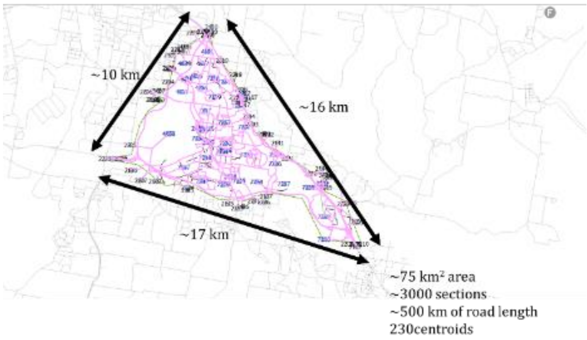



*Figure 2: Study area*

The proposed research is tested on the city of Logan.

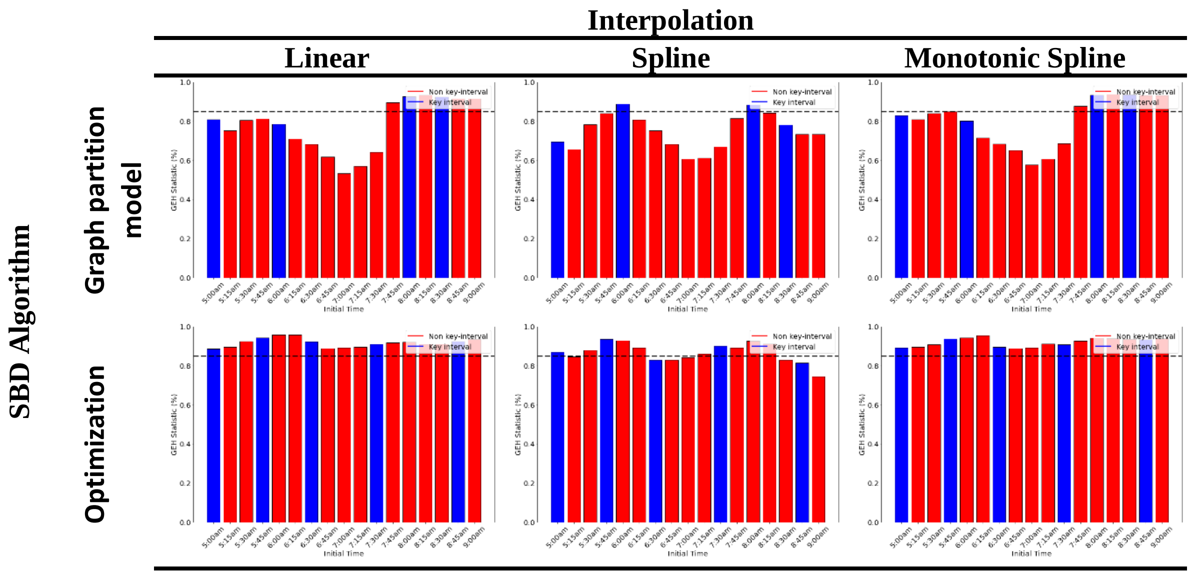
For runtime evaluation purposes, an adjustment scenario for KFI using a standard framework and with split simulation is compared against the state-of-the-art bi-level OD adjustment framework. Table 1 shows the runtime results for each of these scenarios.

Table 1: Runtime results

| Framework | Runtime (s) | $\Delta t$ % |
|---|---|---|
| Bi-level OD adjustment | 7560 | - |
| KFI | 7200 | -4.7% |
| KFI (Split simulation) | 1500 | -80.15% |

Additionally, various algorithms that make up the components of KFI are evaluated in this paper based on the key intervals identified and the travel demand generated using the respective interpolation technique. To isolate assignment errors, the traffic assignment is assumed to be known. Table 2 shows the GEH (<5) statistic results for the Logan city network, evaluated over a 5-hour peak period. The shaded horizontal line shows the industry standard 85% mark as a threshold for acceptable model results. It is to be noted that given the article length constraints, we only highlight the results for the best-performing algorithm in the literature (graph partitioning model) against the new algorithm proposed, which is based on interpolation feedback.

Table 2: GEH statistic results for the Logan city network (5-10 AM peak period)



# 4. DISCUSSION

In this paper, we propose a novel methodology for estimating travel demand and provide background and reasoning for the assumption that accurate OD matrix estimations only require a subset of time intervals. We evaluated this approach on a mid-sized network for the Logan City area and showed that the novel approach could perform well, provided that the optimization-based approach to identify the key intervals is used. We also note that without affecting the process through which the assignment is generated, the upper-level adjustment on a smaller set of intervals only reduces the overall runtime by ~5%. However, only generating the assignment matrices for the required key intervals shows a significant reduction in the runtime (~80% reduction).

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