

Estimating bus passenger loading in London using Automated Fare Collection system and Automatic Vehicle Location system

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I. Introduction

“**The passenger load** is simply the number of passengers on a single transit vehicle ” (Transport Research Board, 2003).

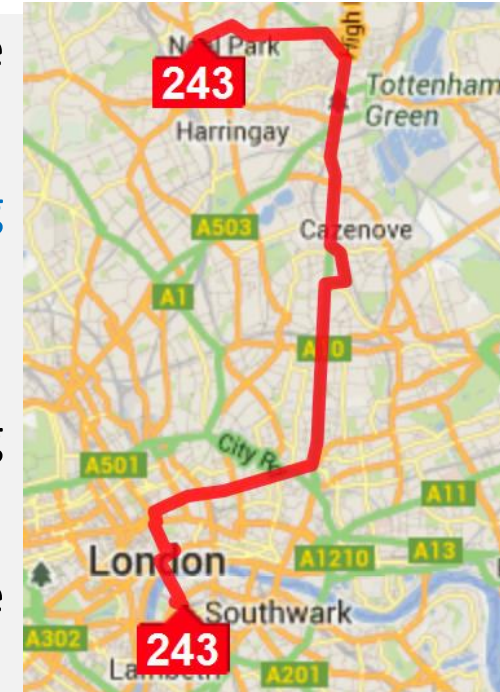
Bus passenger loading is valuable information for bus **operation planning** and **bus service management**.

Objectives

- Explore possibilities for improving passenger loading estimates using new on-board technologies and new supporting algorithms.
- Evaluate a proposed new methodology and its accuracy using a case study on a bus route in London.

Scope

- Bus route 243 in London from Redvers Road to Waterloo Station/Mepham Street (16.5km long with 59 stops for each direction).
- Oyster card data and iBus data on 10th July, 2013.
- Manual surveys on 10th July, 2013.



II. Data collection

1. Oyster card is a 'contactless' smartcard (Automated Fare Collection system).

Oyster card data: 37, 874 Oyster transactions on bus route 243 of 29,005 Oyster card holders are recorded on 10th July, 2013 (provided by Transport for London).

Table 1: Oyster card data sample

Card number	Transaction time (in minute after midnight)	Sequence number of transaction	Boarding Bus stop ID
1	666	18503	2080
2	764	10091	26425
3	949	111	1116
...
19	368	5995	10948
19	805	5996	318
...

II. Data collection

3. Manual survey

- 4 trips (trip 68, 119, 138 and 191) were observed by 2 surveyors from 8:51 to 15:47 on 10th July, 2013.
- The surveyors boarded a bus at the beginning of the bus route, alighted the bus at the destination of the bus route and observed the following data fields for every bus stop.

Table 3: Manual survey sample

No	Bus stop name	Arrival time	Boardings	Alightings	Departure time
1	Waterloo Station/Tenison Way	8:51:44	73	0	8:55:15
2	Waterloo Bridge/South Bank	8:57:21	0	0	8:57:21
3	Lancaster Place	8:58:43	0	0	8:58:43
4	Aldwych/Drury Lane	9:01:10	2	2	9:01:20
...

II. Methodology

1. Boarding inference

- Expected value of Oyster transaction time is assumed to be equal to the value recorded in the Oyster database **plus 30 seconds**.

- Match Oyster transaction times with iBus arrival/departure times to infer boarding **bus trip number for each Oyster transaction**.

- Using **MATLAB** (Matrix Laboratory) program to look up **bus trip number** according to the process (see figure 1).

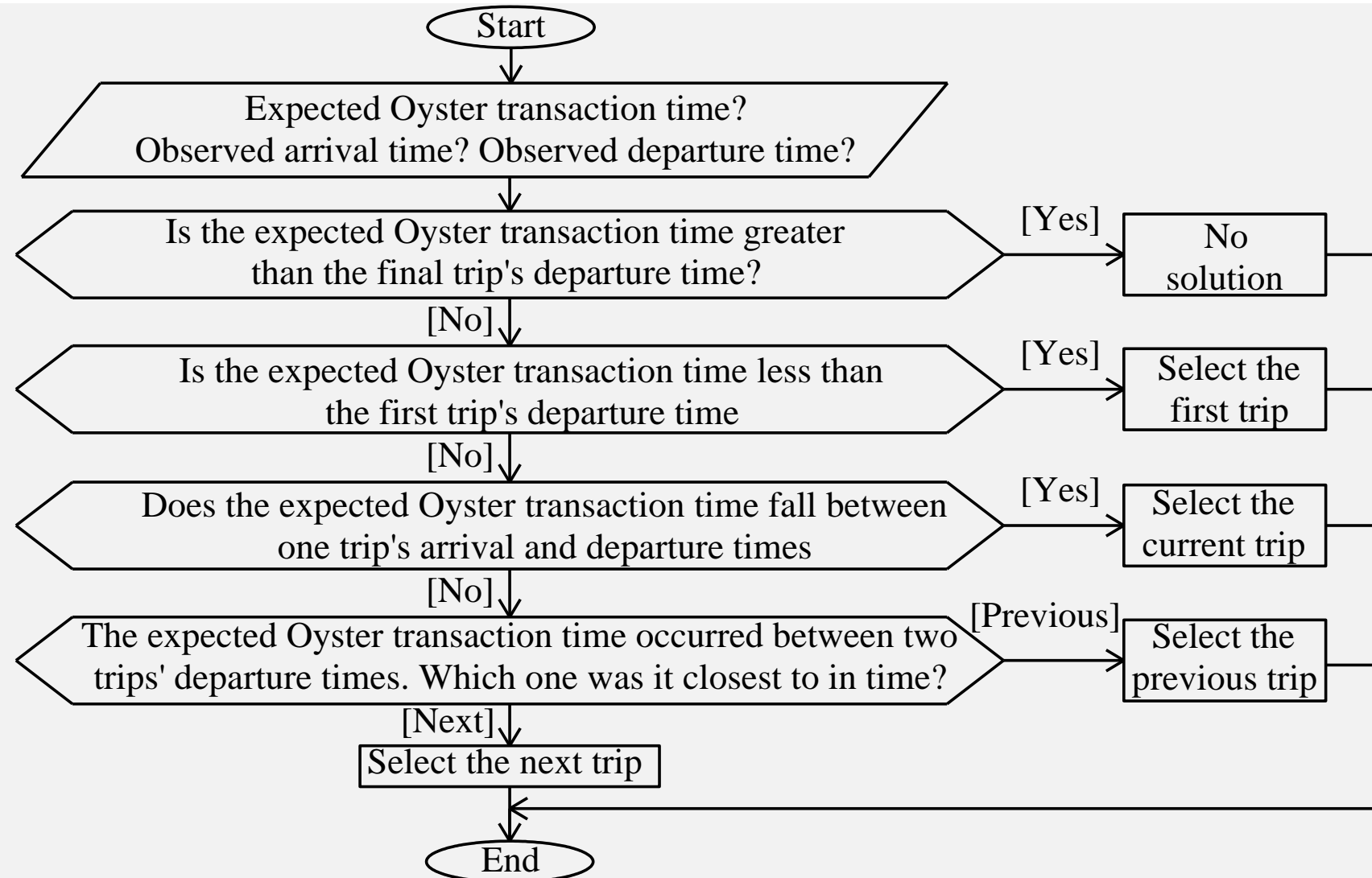


Figure 1: Diagram of boarding inference

II. Methodology

2. Alighting inference

- Each Oyster transaction has ID card, bus trip number, transaction time and boarding stop.

- Assumptions:

(1) Alighting stop of a journey is boarding stop of the next journey.

(2) Alighting stop of the last journey of day is boarding stop of the first journey of day.

- Using MATLAB program to look up alighting bus stops according to the process (see figure 2).

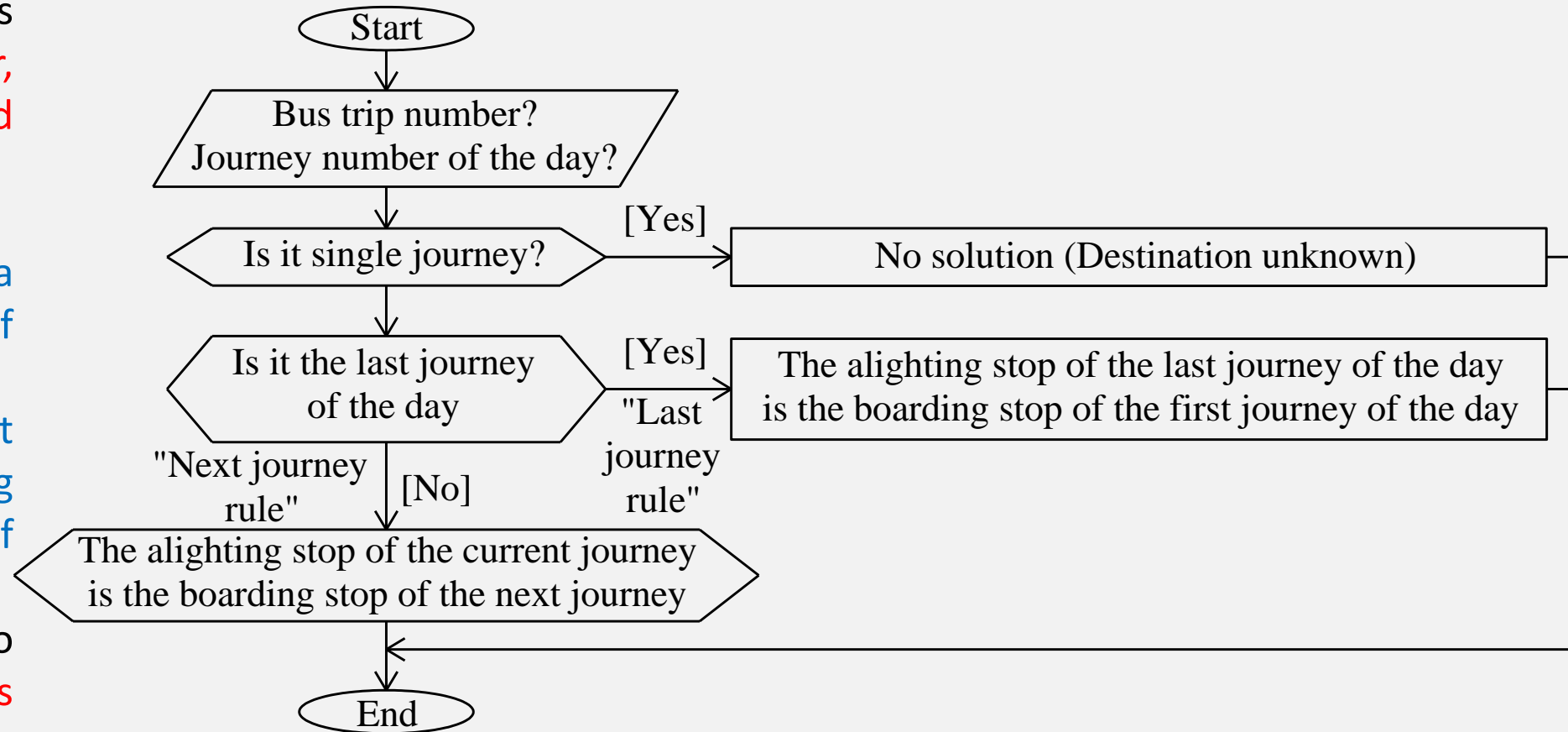


Figure 2: Diagram of alighting inference

II. Methodology

3. Loading estimation

- Inferred boardings and alightings at each bus stop are expanded to ensure that:

- ✓ Non-Oyster passengers are taken into account (multiplied a factor of 1/94.6%, see Table 4).
- ✓ Total boardings and alightings for one completed trip are the same.

- For each data of one trip, bus passenger loading at bus stop j is calculated:

$$L_{i,j} = \sum_{k=1}^j (B'_{i,k} - A''_{i,k}) \quad (1)$$

Where:

- ✓ $L_{i,j}$ is the number of loadings for bus trip number i at bus stop number j .
- ✓ $B'_{i,k}$, $A''_{i,k}$ are the number of expanded boardings and expanded alightings for bus trip number i at bus stop number k ($k = 1, 2, 3, \dots j$).

III. Results from automated data

1. Boarding inference

- 36,937 (97.5%) of Oyster transactions are inferred to have origins and bus trips.

Table 4: Total inferred boardings for 4 trips 68, 119, 138 and 191

Trip number	Total inferred boardings	Total actual boardings	Inferred Percentage
68	178	184	96.7%
119	120	127	94.5%
138	142	152	93.4%
191	147	157	93.6%
Total	587	620	94.6%

2. Alighting inference

- 14,173 of 36,937 transactions (38.4%) have destinations inferred.

- Reasons: 57.9% of transactions were single journey and 3.7% of transactions have invalid inferred results.

3. Loading estimation

- 322 bus trips are scheduled on 10th July, of which 305 have loading estimation.

- The remaining 17 include 14 early trips after midnight 11th July and 3 trips missing iBus data.

IV. Comparison of boarding, alighting and loading between automated data and manual survey data

1. Boarding comparison

- Results for trip 68, 119, 138 and 191 show that inferred boardings at each bus stop can be **very close** to actual boardings.

- Thus the boarding inference methodology has **acceptable accuracy**.

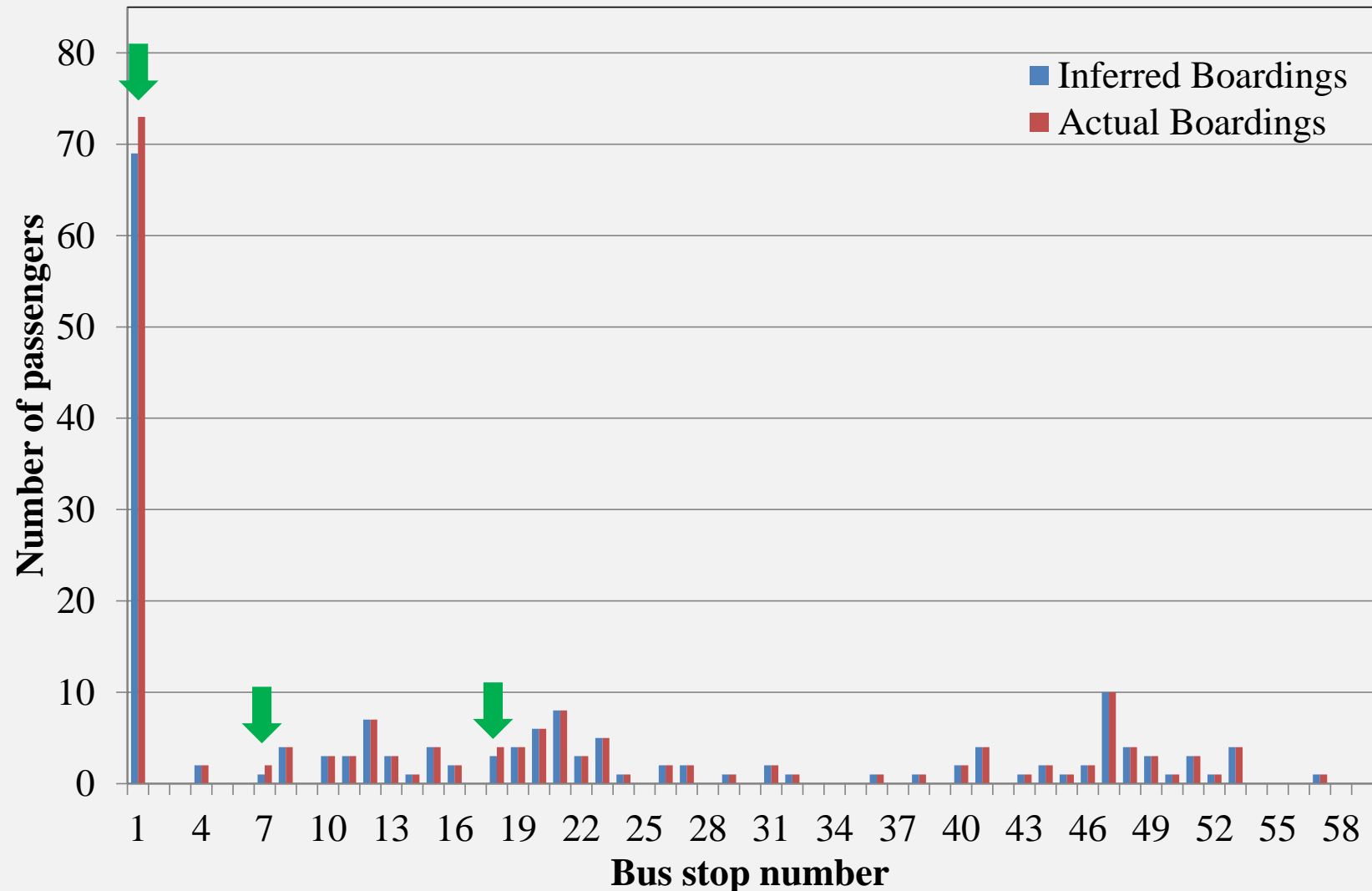


Fig. 3 Boarding comparison for trip 68

IV. Comparison of results between automated data and manual survey data

2. Alighting comparison

- Results suggest that range of alighting difference are mainly from **zero to 3 passengers**, except few differences of 4 to 6.
- Therefore, the alighting inference methodology might be **accurate enough**.

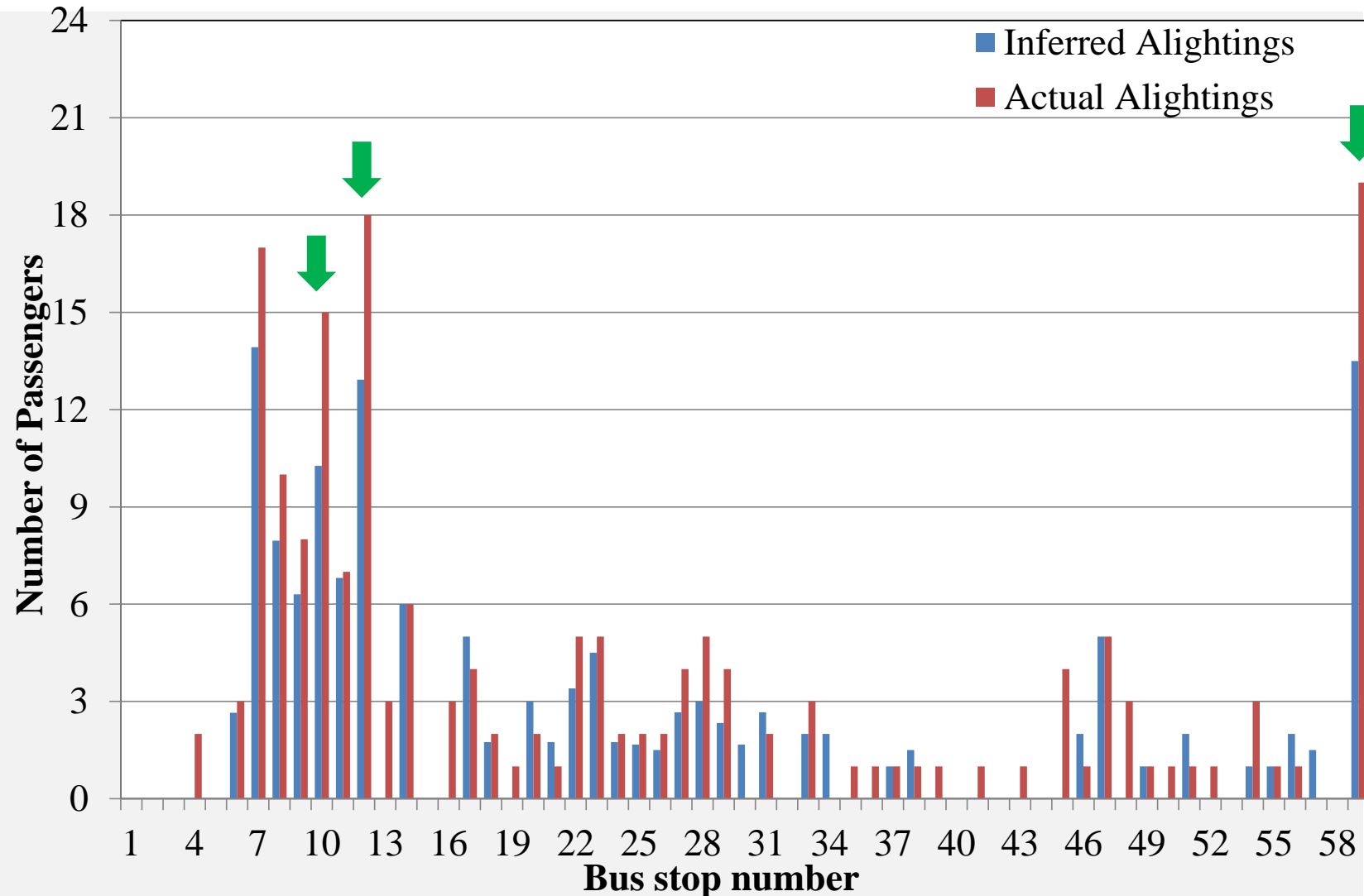


Fig. 4 Alighting comparison for trip 68

IV. Comparison of results between automated data and manual survey data

3. Loading comparison

- Results indicate that estimated loadings and actual loadings are **similar** along the route, although **few large differences in short segments**.

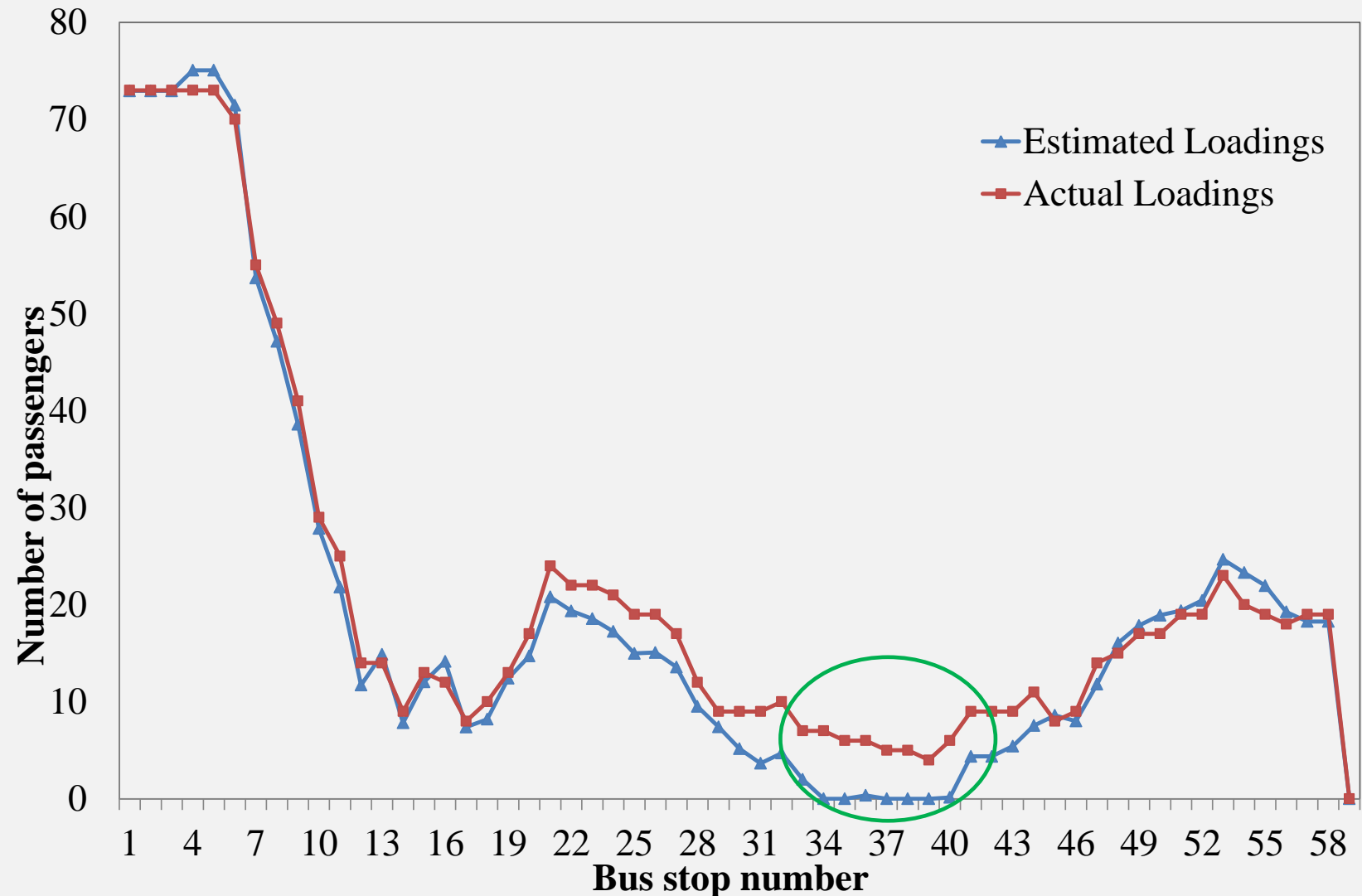


Fig. 5 Loading comparison for trip 68

V. Prediction model of bus passenger loading in real time

1. Prediction model

- The model can be developed by using an algorithm based on **average alighting rate** and **boardings**.
- **Alighting rate**, which is the ratio of alightings to loadings at each bus stop, is identified from historical Oyster data and iBus data. **Average alighting rate** presents for **different time periods of day**.
- Loadings at next bus stop can be predicted **in real time**:

$$FL_{(i+1),j} = FL_{i,j} - AAR_{(i+1),j} \times FL_{i,j} + B^*_{(i+1),j}/0.946 \quad (2)$$

Where:

- $FL_{(i+1),j}$ is number of forecasted loading at bus stop number (i+1) for the trip in period j.
- $FL_{i,j}$ is number of forecasted loading at bus stop number i (previous stop) for the trip in period j.
- $AAR_{(i+1),j}$ is average alighting rate at stop number i for period j, which is estimated from historical data.
- $B^*_{(i+1),j}$ is number of boardings at stop number (i+1) for the trip **in real time**. The number can be calculated **in real time** through the ticket machine after Oyster card holders tap their cards on the card reader.
- $(1/0.946)$ is adjusted to take into account of non-Oyster passengers (see Table 4).

V. Prediction model of bus passenger loading in real time

2. Applying the prediction model to three trips 68, 138 and 191

- This model is applied for **each direction** during **different time periods**.
- Applying the model to trip 191 (direction 1, Midday); trip 68 (direction 2, AM peak) and trip 138 (direction 2, Midday) to test its accuracy.
- **Conclusion:** forecasted data are **consistent** with manual data, though few inconsistencies for **short segments**.

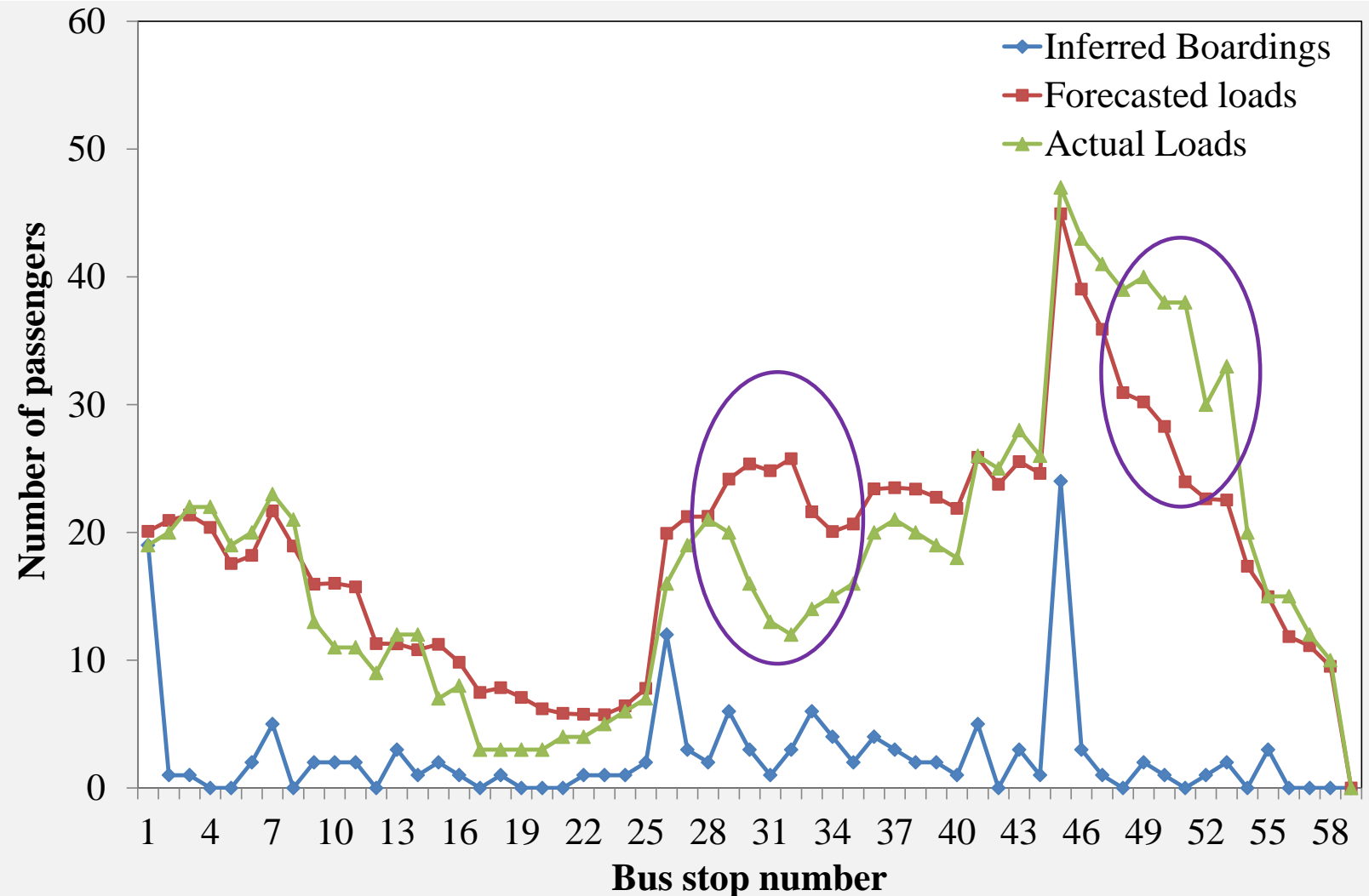


Fig. 6 Comparison between forecasted loads and actual loads for trip 191

V. Prediction model of bus passenger loading in real time

3. Hypothesis testing

- A Paired-Samples T Test is carried out to test that **forecasted loads and actual loads** of each bus trip are **the same** at **59 bus stops**.

- Let's create a variable $D_i = FL_i - AL_i$ (3)

Where:

- D_i is difference in passengers between forecasted loads and actual loads at bus stop number i .
- FL_i, AL_i are the number of forecasted loads and actual loads at bus stop number i .
- Null Hypothesis is $H_0: \delta = 0$.
- Alternative Hypothesis is $H_1: \delta \neq 0$ (Two sided alternative hypothesis). Sample size: $n = 59$.
- This test is carried out by using **SPSS program**.
- Results: P value for trip 191 is **0.428** > **0.025** (test point) and the values for trips 68, 138 are **0.000**.
- Conclusion: There **is no evidence** (at the 5% level) **to reject** the suggestion that forecasted loads and actual loads of bus trip 191 are the same at 59 bus stops. Whilst the suggestions for trip 68 and 138 **are rejected**.

VI. Conclusion and recommendations

1. Key findings (1)

- The methodology for boarding/alighting inference and loading estimation using AFC/AVL systems has acceptable accuracy.
- This prediction model of loading in real time is suggested as an approximate application rather than an absolute one, and is feasible in reality.
- This study might be helpful for London bus planners to evaluate some bus route standards such as maximum standees, standees versus no-standees and duration of standee time, bus capacity and bus frequency.

VI. Conclusion and recommendations

1. Key findings (2)

- **This method** of estimating bus passenger loading and **this prediction** model can be **potentially** transferred and implemented in **other major cities** in Europe, the United States and South America, **Asia** where AFC system and AVL system are being operated in transit agencies.
- **Hanoi**, the capital of **Vietnam**, is a feasible case. Smart card system and AVL system have begun to be equipped for **only bus route 6 since 2014**. After collecting historical smart card data and AVL system data for the route 6, this method might be used feasibly.

2. Recommendations

- More complete and accurate iBus data: a system or supervisors at the bus control centers are necessary to remind drivers to **log in/off** on the bus **iBus system on time** at the beginning/end of a completed trip.
- Improve the temporal precision of recorded **Oyster transactions**, which should be shown **in seconds**.

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Thank you for listening!

Questions and Answers?