An Analysis of Bus Ticket Sales in East Bangalore

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Abstract

This paper investigates different aspects of demand modelling for bus transport systems based on the data obtained from Electronic Ticketing Machine(ETM). Nowadays, ETM′s have been introduced by many Public Transit Agencies as part of improving their operations and services. The data used in this study is the ticket sales data from the Bangalore Metropolitan Transport Corporation(BMTC)[1]. BMTC approximately makes 69000 vehicle trips with a traffic revenue of Rs5.17 crores everyday. The ETM data of BMTC has approximately 40 million transactions per month. This ETM data can be utilized effectively to understand passenger movement, identification of peak and off-peak hours of the day, popular Origin-Destinations, operator's efficiency in terms of revenue generated, load-profiles at 1. route-level, 2.corridor-level, 3. Origin-Destination(OD) wise etc across Bangalore. This paper focuses on generation of Origin-Destination matrices from this ETM data to understand the user behaviour between different ODpairs, duration of peaks and off-peaks for the ODpairs across the different times of the day. This OD data will help in understanding the spatio-temporal bus ridership demand in Bangalore. The work presented in this paper provides details on the methodology for generating the ODmatrix and additional inferences that are possible from the ETM data. This work also presents a number of analysis tasks that were executed, to derive information from ETM data for travel demand modelling and operational planning of public transit agencies. A major finding is that while nearly two thirds of ticket sales happen during peak period, peak periods themselves were a small fraction of the overall operating hours.

1 Introduction

Urbanization has resulted in greater demand for movement of people and goods which mandates good mobility within the city. Public Transport plays an important role in mobility in any city. Transportation Planners are often required to analyze various parameters to ensure effective services. Bangalore Metropolitan Transport Corporation(BMTC) is the public bus transit operator in Bangalore in India. There are around 6600 buses with around 2500 routes that are operated in the city. These buses are equipped with automatic vehicle location system(GPS) and electronic ticketing machines. To attract more people, public bus transport-the fleet operator

[1]https://www.mybmtc.karnataka.gov.in/info-1/BMTC-Glance/en

should provide quality service to passengers. It is important to estimate the demand for public transit which in turn affects the operational policies and strategies of the public transit agency. Appropriate estimation of the peak and off-peak time, peak and off-peak loads leads to better understanding and modelling of the travel demands and operations.
The ETM is a handheld device that records the transaction when a passenger requests a ticket. The introduction of the Automated data collection source like Electronic Ticketing Machine(ETM) plays a vital role in the absence of smart cards or travel cards in Bangalore. Hence, building tools to explore this ETM data and asking the right analytic questions provides us with the better understanding of the passenger movement and therefore system's behaviour. Bangalore has two types of ticketing system: 1. trip based tickets, and 2. pass-tickets. The pass-tickets can be one of the following: 1. Student pass, 2. Day pass, 3. Monthly pass, or 4. Senior Citizen. Every transaction in BMTC-ETM captures data like Ticket_id, waybil_Id, waybill_no, schedule_no, trip_no, etim_no, route_no, route_id etc. Using these, various key performance indicators like Total number of passengers [route-level,Daily], High boarding/alighting stops, In-vehicle passenger volume or Occupancy, Occupancy ratio, Average revenue per shift etc can be computed to know the effectiveness of the services provided.

2 Related Literature

There are many factors like speed of the bus, schedule adherence,passenger demand, travel time etc that affect the effectiveness of public travel. One of them is passenger demand. Passenger demand modelling and estimation is one of the important task in transport operations. The conventional method of data collection like household surveys, travel surveys to understand the demand are both expensive and time consuming and hence they are infrequent[Cui07]. Also, surveys would be conducted on few sample routes or links or zone and hence the comprehensive view of existing demand of a city may not be understood completely. In contrast, there is a need for frequent analysis and updating of real time traffic scenarios to improve the public transport operations. Hence, the Automated Data Collection(ADC) systems have gained importance. The Automated Data Collection(ADC) systems include Automatic Passenger Counting(APC)[Fur06], Automatic Vehicle Location(AVL)[Fur06] and Automatic Fare Collection(AFC)[Nun17]. Smartcard data[Ort15], cellphone data [Dem17] and social media data are some of the other data sources that are being used now-a-days to understand the travel demand. There are a lot of literature available that explore ADC data to understand the system.
Yu et al[Sha16] have proposed to forecast bus passenger trip flow for transit route design and optimization. They have used Aritificial Neural Network(ANN) to forecast the bus passenger trip flow and have validated with a dataset from China. The ANN model is based on the influence factors like each traffic zone land use (the proportion of residential, commercial and industrial traffic), accessibility to bus stations, area and distance between zones etc. They have used the OD pairs as a base from a survey that was carried out to forecast the passenger flow. Kinene [Kin09] employed Random Forest machine learning algorithm to predict the hourly demand for buses along all routes in ´Orebro city in Sweden. They have considered factors like day of the week, weather season, time of the day, customer types etc for predicting the hourly demand for buses. Kinene also suggests that these information can be used to decide the frequency on a given route considering these factors. Cui[Cui07] in his thesis has developed an algorithm to estimate bus passenger ODmatrix using the data from Automatic Vehicle location(AVL) and Automated Fare Collection(AFC). Initially, a single route ODmatrix is estimated from a seed matrix that is derived from AFC data. Then Iterative Proportional Fitting and Maximum Likelihood Estimation(MLE) techniques are used to estimate ODmatrix for single routes. Then network level ODmatrix are estimated. Ji et al [Yji17] have proposed Hierarchical Bayesian model to estimate the trip-level OD flows and a period-level OD flow from the samples OD flow data collected by the WIFIsensors and the fareboxes. They have used bus load and average journey length to reflect indirectly on the accuracy of their proposed OD estimation method. Li et al[Dli11] also have proposed an OD estimation matrix for each route using the data collected from the farebox. They have presented an OD estimation model based on trajectory search algorithms to track passenger trips, using the pre-processed smart card data. They have used one day smart card data from Jinan city. They also suggest that the estimated ODpairs can be used to evaluate route network and optimize bus scheduling. Janine[Jan08] has also proposed to construct Automated Bus Origin-Destination matrix using farebox and AVL data.
Most of the works in literature for travel demand analysis are based on the Automatic Fare Collection(AFC) or Farebox. The data that we have analyzed is from Electronic Ticket Machines(ETM) which has few more details than that of Farebox. A few works are available in literature that analyze data from ETM machines. Cyril et all[Cyr17] have analyzed ETM data of Kerala State Road Transport Corporation for 6 depots in Trivandrum

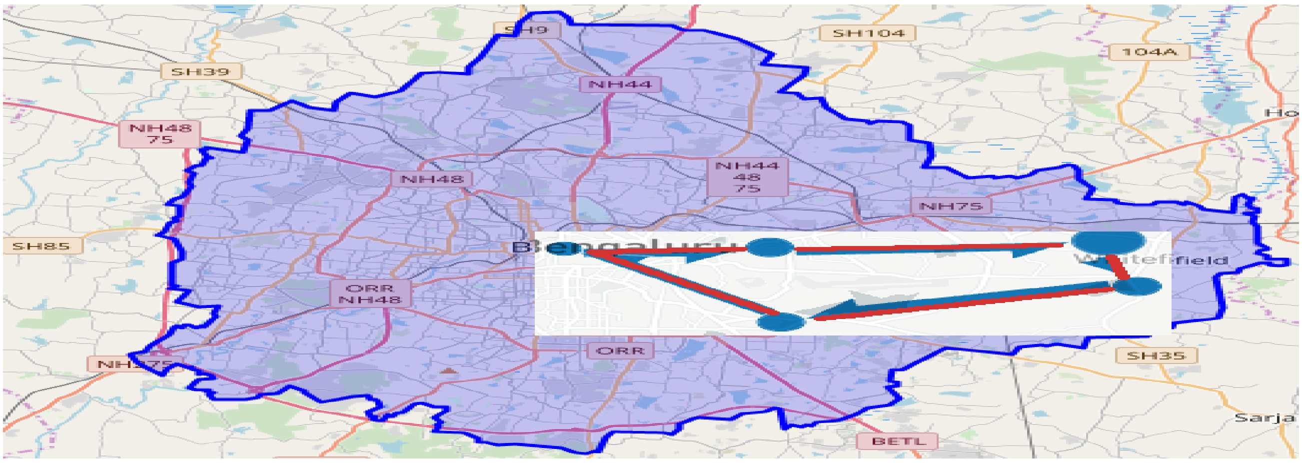


Figure 1: Bangalore map and Area of study-East Bangalore as outlined by red

city for modelling intercity public transport demand to predict the number of trips on a given day. Kalanidhi et al[Kal13] have used ETM data along with OD pattern of travels taken from Chennai City Traffic Study of Chennai Meteropolitan Development Authority, passenger opinion survey and GPS data to study the accessibility of urban trnasportation networks and assessing its influence on the public transport ridership. Wang et al[Wan11] have proposed a methodology to infer bus passenger travel behaviour, ODpair inference using the smart card transactions and AVL data in London.
In this study the objective is to analyze the ODpairs to understand the passenger distribution and hence to obtain the temporal and spatial variation in ridership and hence passenger travel characteristics. This paper focuses on generating the passenger movement from the ETM data and some of the key performance indicators like Total number of passengers [route-level,day-level], load profiles of routes, identification of peak and off-peak hours based on the number of tickets sold.

3 East Bangalore - A case study

This section presents the area of study and provides details on the data collected and the methodology used to generate the ODpairs. Bangalore is the fifth largest urban city in India with a population of about 8.5 million as of 2011 with an area of 709 sq km. The below map shows the boundary of Bangalore and the portion highlighted in red is the study region which is East-Bangalore[2] BMTC is the government agency that operates public transport bus service in Bangalore. It has different types of services like 1. General, 2. Samartha, 3. Suvarna, 4. BIG 10, 5. Big Circle, 6. Atal Sarige, 7. Vajra, 8.Vayu vajra, 9. Marcopolo and Corona AC, 10.Metro Feeder and 11. Hop On Hop Off. These BMTC buses are operated from 48 depots[3] within the city and are numbered from 1 to 48. In some BMTC services, the tickets are issued using a Electronic ticket machine(ETM) and in few other services, the manual(pre-printed) tickets are issued. This study analyzes both ETM data and manual ticket data sold in buses operated from four depots 6, 25, 28 and 41, which cater to the East Bangalore population. In the introduction, it was mentioned that two types of tickets - trip based tickets and pass tickets are available in BMTC. This study focuses only on trip based tickets as the information about the travel made by pass ticket holders in not available. It is assumed that the analysis results could be a representative of the total public transit passengers. BMTC is the government agency that operates public transport bus service in Bangalore. It has different types of services like 1. General, 2. Samartha, 3. Suvarna, 4. BIG 10, 5. Big Circle, 6. Atal Sarige, 7. Vajra, 8.Vayu vajra, 9. Marcopolo and Corona AC, 10.Metro Feeder and 11. Hop On Hop Off. These BMTC buses are operated from 48 depots[4] within the city and are numbered from 1 to 48. In some BMTC services, the tickets are issued using a Electronic ticket machine(ETM) and in few other services, the manual(pre-printed) tickets are issued. This study analyzes both ETM data and manual ticket data sold in buses operated from four depots 6, 25, 28 and 41, which cater to the East Bangalore population. In the introduction,

[2]East-Bangalore was identified as study region since ticket sales data was predominantly available for this region from the 4 depot's data and is not exclusive of east bangalore region.
[3]https://www.mybmtc.karnataka.gov.in/info-1/Depots/en
[4]https://www.mybmtc.karnataka.gov.in/info-1/Depots/en

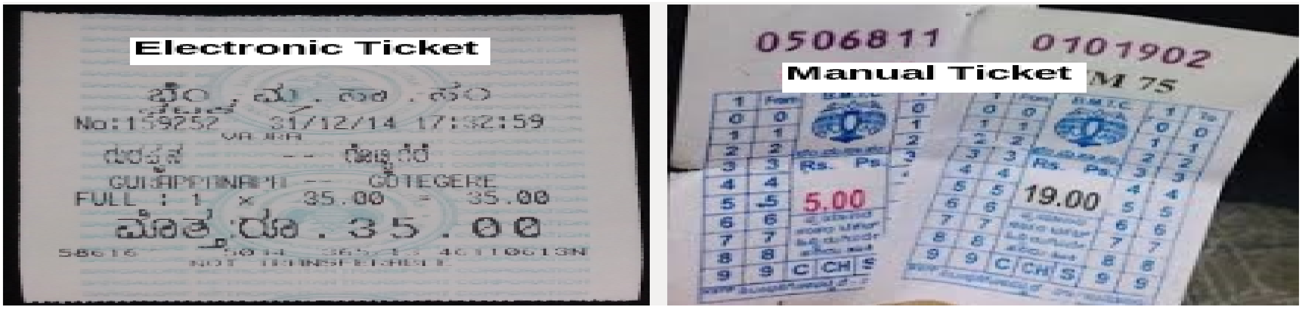


Figure 2: Caption

Table 1: Ticket Parameters Studied

Parameter	Explanation
Ticket_from_stop_id	Origin stop for the ticket sold
Ticket_till_stop_id	Destination stop for the ticket sold
Schedule_no	Bus Schedule number
Trip_no	Trip number of the schedule
Vehicle_no	Vehicle number of the bus[KA01F9372
Ticket_type_short_code	Code for type of ticket sold [Trip start / Trip close / Passenger / Luggage / Group / Pass / Penalty / Stage close / Toll pass etc]
Ticket_sub_type_short_code	Subtype of the ticket sold like [Adult / Child / Heavyweight / Lightweight / Daily Pass etc]
px_count	Number of passengers
Total_ticket_amount	Amount of the ticket sold
Ticket_from_stop_seq_no	Within the route, stop_no from where the passenger boards the bus
Ticket_till_stop_seq_no	Within the route, stop_no where the passenger alights from the bus
Ticket_printed_flag	Whether the ticket was printed
Ticket_date	Ticket issue date
Trip_direc	Trip direction whether it is forward(UP) or backward(DN)

it was mentioned that two types of tickets - trip based tickets and pass tickets are available in BMTC. This study focuses only on trip based tickets as the information about the travel made by pass ticket holders in not available. It is assumed that the analysis results could be a representative of the total public transit passengers.

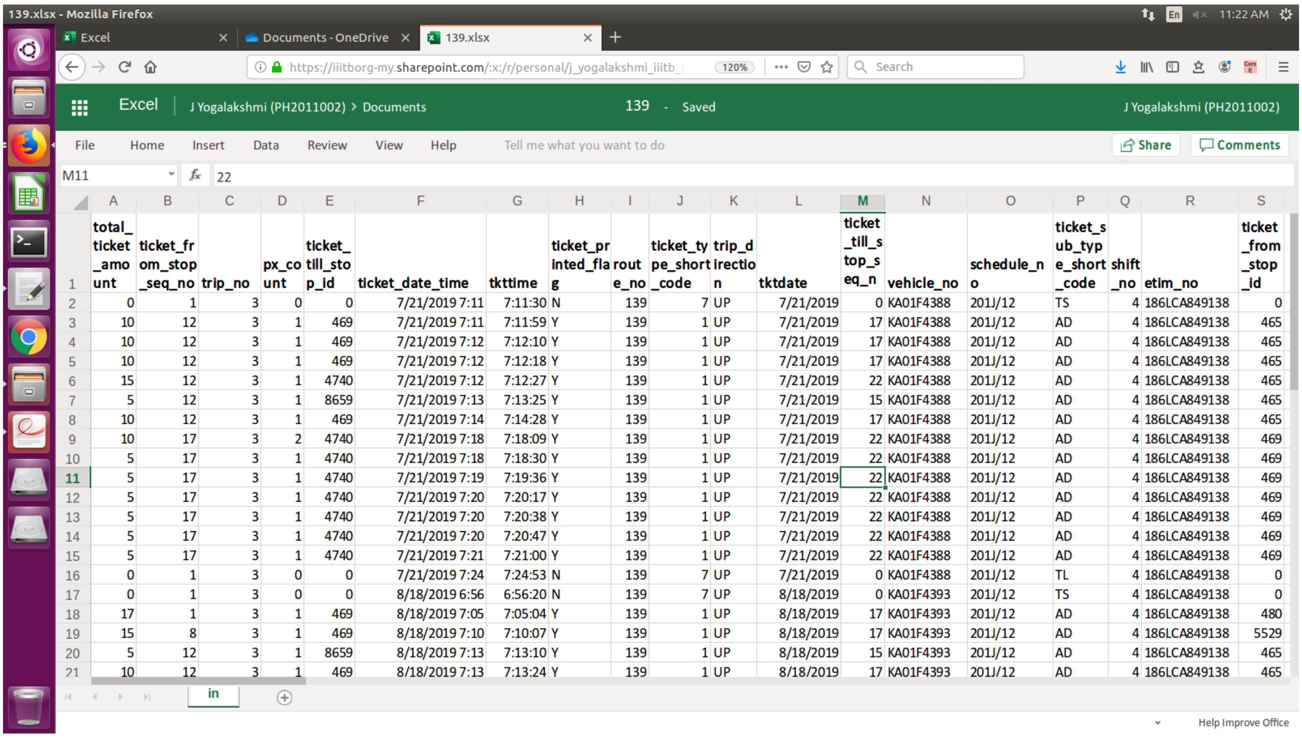
3.1 Electronic Ticketing Machine

The Electronic ticket machine(ETM) is a handheld device which weighs about 800gms. They are GPRS[5] enabled ETM which transmits ticket data to ITS server every 5minutes. The figure 2 shows both ETM and manual ticket. When a ticket is issued using the ETM, there are as many details as 50 parameters, that are sent to the data server that is placed in BMTC data center. The parameters that we have analyzed are given in Table 1.

3.2 Data Collection and Pre-processing

The ETM data along with data in manual tickets for the month of December 2018 and July 2019 from depots $6, 25, 28$ and 41 was provided to us for analysis. Each data file size was between 250MB to 800MB. Each data file had 59 parameters including: ticket_id, waybil_Id, waybill_no, schedule_no, trip_no, etim_no, route_no, route_id, transaction_no, ticket_no, ticket _type_short_code, ticket_sub_type_short_code, ticket_from_stop_id,

[5] General Packet Radio service https://www.gsmarena.com/glossary.php3?term=gprs



	total_ticket_amount	ticket_from_stop_seq_no	trip_no	px_count	ticket_till_stop_id	ticket_date_time	tkttime	ticket_printed_flag	route_no	ticket_type_short_code	trip_direction	tktdate	ticket_till_stop_seq_n	vehicle_no	schedule_no	ticket_sub_type_short_code	shift_no	etim_no	ticket_from_stop_id
2	0	1	3	0	0	7/21/2019 7:11	7:11:30	N	139	7	UP	7/21/2019	0	KA01F4388	201J/12	TS	4	186LCA849138	0
3	10	12	3	1	469	7/21/2019 7:11	7:11:59	Y	139	1	UP	7/21/2019	17	KA01F4388	201J/12	AD	4	186LCA849138	465
4	10	12	3	1	469	7/21/2019 7:12	7:12:10	Y	139	1	UP	7/21/2019	17	KA01F4388	201J/12	AD	4	186LCA849138	465
5	10	12	3	1	469	7/21/2019 7:12	7:12:18	Y	139	1	UP	7/21/2019	17	KA01F4388	201J/12	AD	4	186LCA849138	465
6	15	12	3	1	4740	7/21/2019 7:12	7:12:27	Y	139	1	UP	7/21/2019	22	KA01F4388	201J/12	AD	4	186LCA849138	465
7	5	12	3	1	8659	7/21/2019 7:13	7:13:25	Y	139	1	UP	7/21/2019	15	KA01F4388	201J/12	AD	4	186LCA849138	465
8	10	12	3	1	469	7/21/2019 7:14	7:14:28	Y	139	1	UP	7/21/2019	17	KA01F4388	201J/12	AD	4	186LCA849138	465
9	10	17	3	2	4740	7/21/2019 7:18	7:18:09	Y	139	1	UP	7/21/2019	22	KA01F4388	201J/12	AD	4	186LCA849138	469
10	5	17	3	1	4740	7/21/2019 7:18	7:18:30	Y	139	1	UP	7/21/2019	22	KA01F4388	201J/12	AD	4	186LCA849138	469
11	5	17	3	1	4740	7/21/2019 7:19	7:19:36	Y	139	1	UP	7/21/2019	22	KA01F4388	201J/12	AD	4	186LCA849138	469
12	5	17	3	1	4740	7/21/2019 7:20	7:20:17	Y	139	1	UP	7/21/2019	22	KA01F4388	201J/12	AD	4	186LCA849138	469
13	5	17	3	1	4740	7/21/2019 7:20	7:20:38	Y	139	1	UP	7/21/2019	22	KA01F4388	201J/12	AD	4	186LCA849138	469
14	5	17	3	1	4740	7/21/2019 7:20	7:20:47	Y	139	1	UP	7/21/2019	22	KA01F4388	201J/12	AD	4	186LCA849138	469
15	5	17	3	1	4740	7/21/2019 7:21	7:21:00	Y	139	1	UP	7/21/2019	22	KA01F4388	201J/12	AD	4	186LCA849138	469
16	0	1	3	0	0	7/21/2019 7:24	7:24:53	N	139	7	UP	7/21/2019	0	KA01F4388	201J/12	TL	4	186LCA849138	0
17	0	1	3	0	0	8/18/2019 6:56	6:56:20	N	139	7	UP	8/18/2019	0	KA01F4393	201J/12	TS	4	186LCA849138	0
18	17	1	3	1	469	8/18/2019 7:05	7:05:04	Y	139	1	UP	8/18/2019	17	KA01F4393	201J/12	AD	4	186LCA849138	480
19	15	8	3	1	469	8/18/2019 7:10	7:10:07	Y	139	1	UP	8/18/2019	17	KA01F4393	201J/12	AD	4	186LCA849138	5529
20	5	12	3	1	8659	8/18/2019 7:13	7:13:10	Y	139	1	UP	8/18/2019	15	KA01F4393	201J/12	AD	4	186LCA849138	465
21	10	12	3	1	469	8/18/2019 7:13	7:13:24	Y	139	1	UP	8/18/2019	17	KA01F4393	201J/12	AD	4	186LCA849138	465

Figure 3: Route-level ticket sales data for route: 139

ticket_from_stop _seq_no, ticket _till_stop_id, fare_type, upload_flag etc. Out of these only parameters mentioned in Table 1 were required for our analysis.

3.3 Pre-Processing of data files

One data file for each depot(6, 25, 28, 41) was provided consisting of ticket sales of all the routes that operates from the depot. This data file of each depot is processed to check for any inconsistent data type values, spurious rows etc. The data processing steps followed are:

1. From each depot data, generate separate files for every route.
2. Simultaneously, extract only the required parameters of Table 1 for every route.
3. The route-level data files for each depot and month(December2018 and July2019) are extracted separately. This extracted route file data size is of the order of few KBs and becomes the base data for further analysis.

A snapshot of the generated route-level ticket sales data of route **139** is shown in the figure 3

4 Data Analysis

The route-level data files extracted for each depot forms the base data for all our analysis tasks. The following analysis were carried out on these data:

1. Total Number of Passengers route wise and day wise.
2. Hourly occupancy of passengers route wise, day wise and vehicle wise.
3. Load profile - Occupancy trip wise and by stop wise
4. Identification of the location and time of peaks and valleys in the distribution of ticket sales month wise and hence check for any patterns.
5. Distribution of users based on identified Origin-Destination pairs.

4.1 Total number of passengers

The total number of passengers route-level trip-wise, schedule-wise and day-wise computed using a Python script. The sample output for some of the routes are as shown in table 2:

Table 2: Sample output of computed Total number of Passengers

Route _no	**Vehicle_no**	**Ticket_date**	**Total _no;of _pass engers**	**Total _ticket _amount**	**Shift _no**	**Trip _no**	**Scheduled _Start _time**	**Scheduled _End _time**
SBS-13K	KA01FA1881	12/12/2018	3	28	2	1	2018-12-12 12:09:27	2018-12-12 13:06:39
SBS-13K	KA01FA1881	12/13/2018	4	34	2	1	2018-12-13 11:47:51	2018-12-13
SBS-13K	KA01FA1881	12/18/2018	8	55	2	1	2018-12-18 11:15:17	2018-12-18 12:40:11
SBS-13K	KA01FA1881	12/18/2018	6	50	2	1	2018-12-22 12:04:44	2018-12-22 12:32:31
500-QG	KA57F1926	12/29/2018	29	471	2	1	2018-12-29 07:25:45	2018-12-29 08:01:52
500-QG	KA57F1926	12/2/2018	17	281	2	1	2018-12-02 15:46:47	2018-12-02 17:06:30

4.2 Hourly Occupancy

The term **occupancy** of a bus is defined as the following. It is given by:

$$\begin{aligned} Occupancy &= x + y, \text{where} \quad (1)\\ x &= \text{Number of people who are inside the bus when it arrives at a stop,}\\ y &= \text{Number of people boarding the bus at that stop} - \text{Number of people alighting at that stop} \end{aligned}$$

The occupancy at a route level helps to understand the passenger demand in the route at different times of the day. It also helps to understand the peak and off-peak times of the given route. The figure 4 gives the hourly occupancy of route:V$-$500D between December $3^{rd} - 7^{th}$ and figure 5 gives the hourly occupancy of route:SBS$-$1K between December $3^{rd} - 7^{th}$.

It could be observed that the route:V-500D have 2 clear peaks, one in morning between 8.30 A.M to 10.30 A.M and one in evening between 17.30 P.M to 20.30 P.M. Whereas, the route:SBS-1K has a sharp morning peak, but the evening peak relatively blunt compared to the morning peak. These give the times when the routes are most used. Another important factor to observe is that the peak(morning/evening) load is $2 - 3$ times that of the load in off-peak times. This pattern is consistent across all days in the week as shown. The similar pattern is also observed across all weeks of the month. The figure 6 shows the hourly occupancy in V-500D for 4 weeks in December 2018. We could compute Utilization by examining whether the occupancy is $< 100\%$ or $> 100\%$. *This piece of information would be a valuable feedback to be considered by the operations and planning team of public transit agency while scheduling.*

4.3 Load Profile

The load profiles of a route gives a much detailed information such as the trip-wise, stop-wise and time-wise occupancy. These also allow us to infer the trip times of various trips made through out the day and how they vary in peak and off-peak hours of the day. The figure 7 show the different trips made by the route:335C in December $2^{nd} - 7^{th}$. It can be observed that the trips that start between 8.00 A.M and 10.30 A.M take slightly little longer time to complete the trip compared to other trips made in the day.

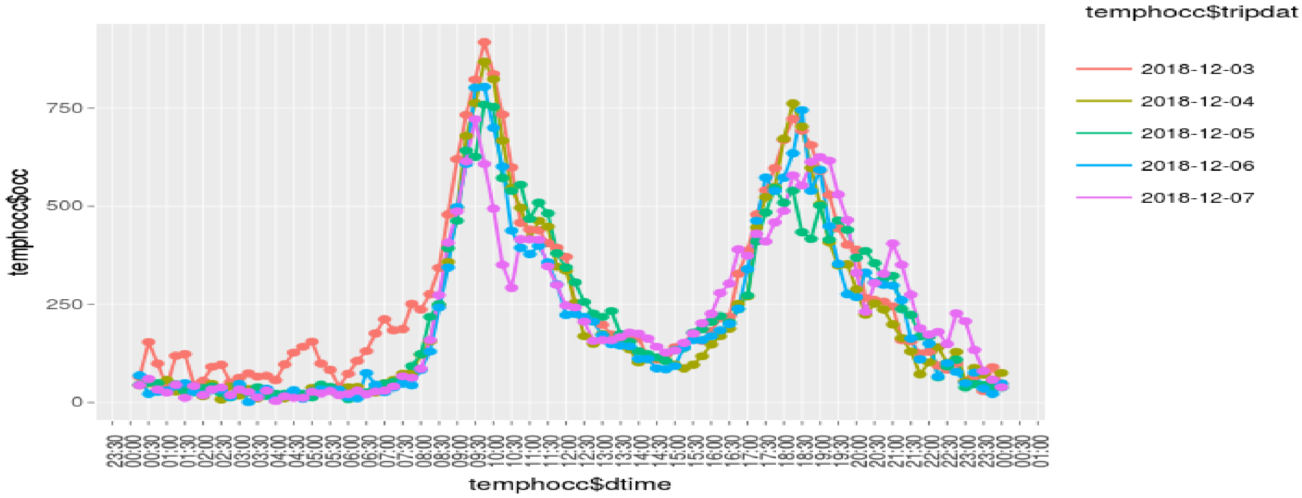


Figure 4: Hourly occupancy on V-500D

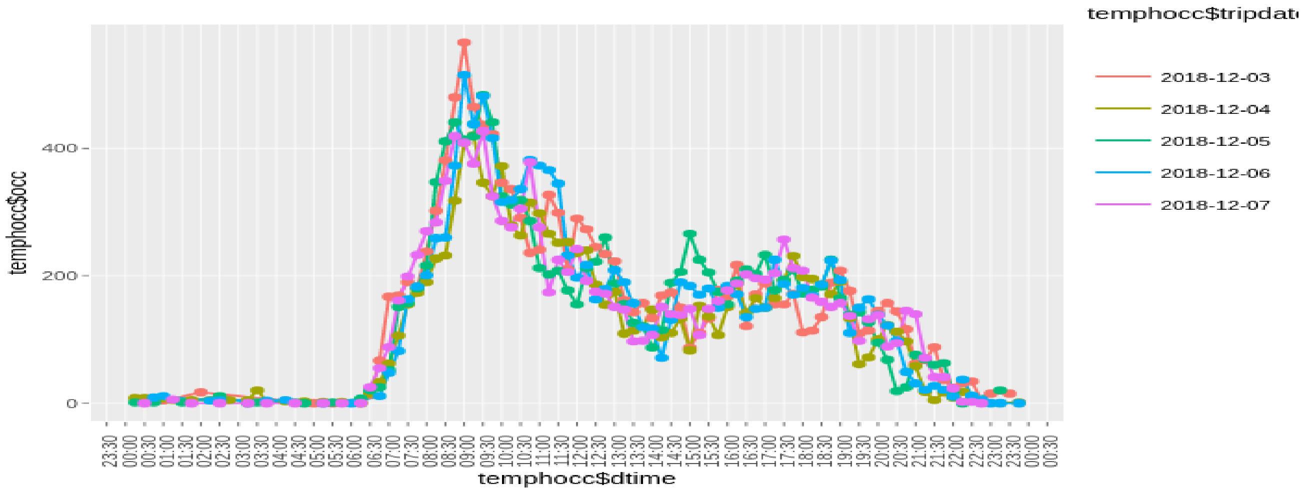


Figure 5: Hourly Occupancy on SBS-1K

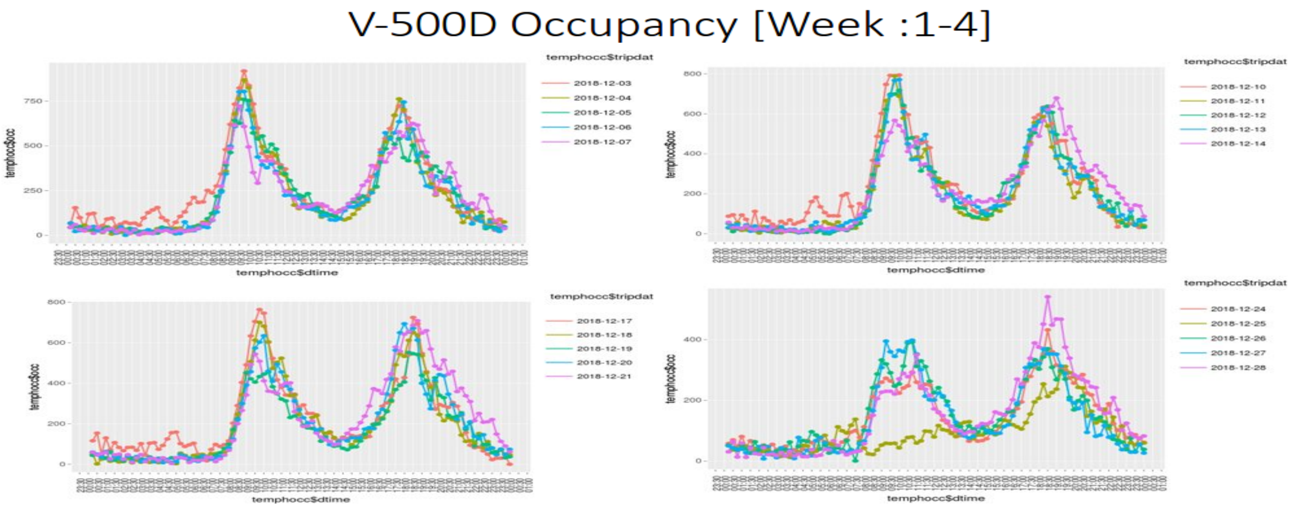


Figure 6: Hourly occupancy on V-500D on 4 weeks in December 2018

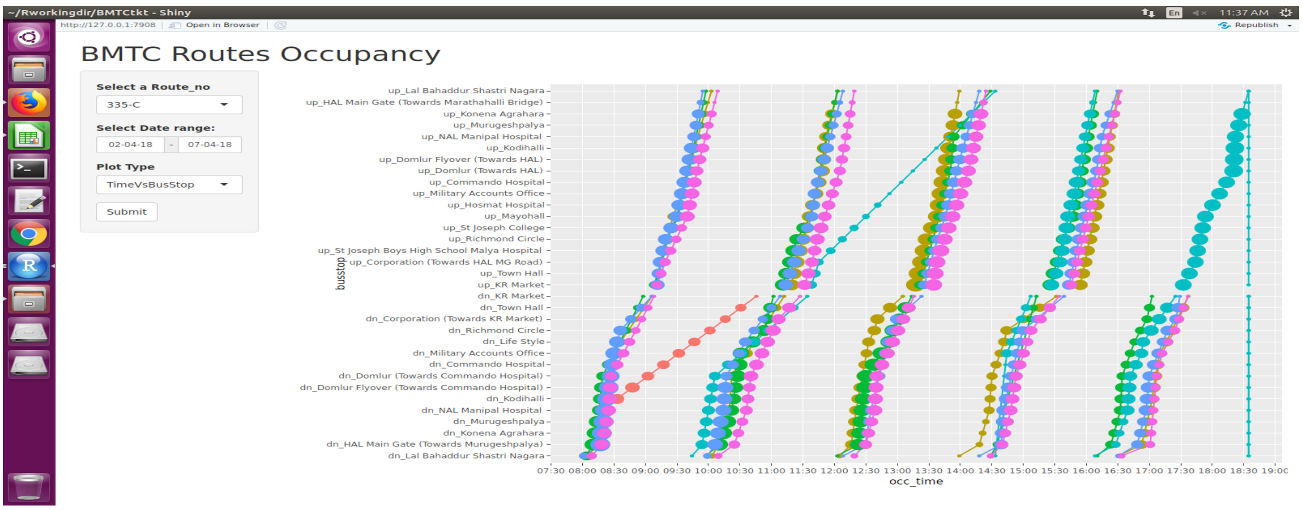


Figure 7: Load Profile of 335C between 2-7th in December 2018

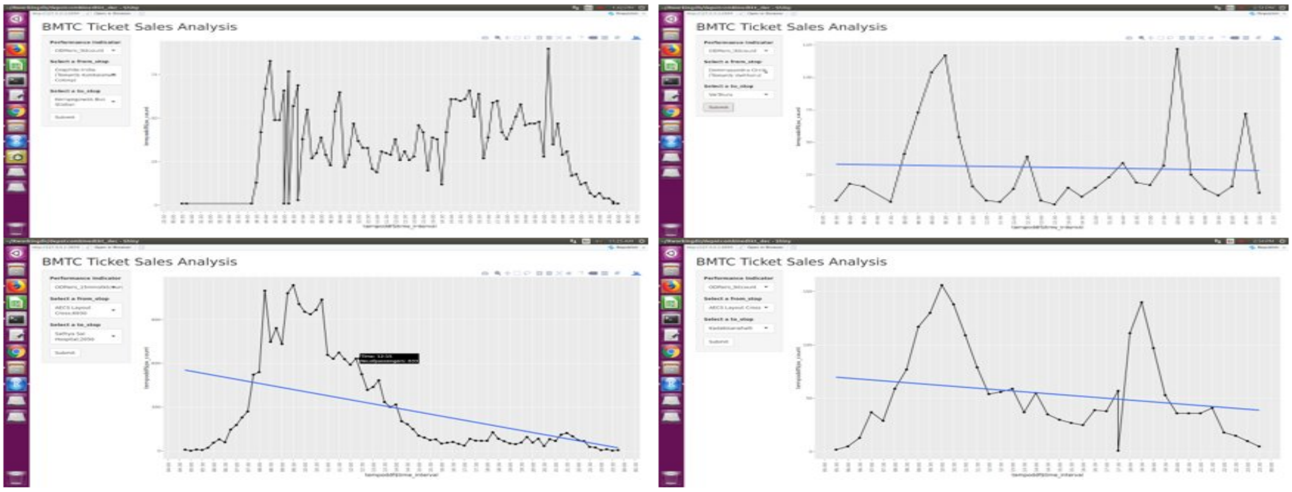


Figure 8: Peak and off-peaks between different ODpairs

4.4 Generate Origin-Destination pairs

The Origin-Destination pairs from the route-level ticket sales data have to generated to understand the spatio-temporal passenger distribution across Bangalore. This also helps in identification of the peaks and valleys in the distribution. The steps followed to generate the ODpairs from the route-level ticket sales data are given below.

1. From the route-level ticket sales data, the distinct Origin-Destination(OD) pairs for every 15 minutes are extracted along with the number of passengers and ticket amount.

2. The ODpairs (same ODpairs could occur in multiple routes) for every 15 minutes for each week(only for weekdays) are generated in separate files.

3. The week-wise files from step no 2 are generated for the months of December 2018 and July 2019 separately.

   There are four weeks in December 2018 : Week_1 : December 3^{rd} to 7^{th} , Week_2 : December 10^{th} to 14^{th}, Week_3 : December 17^{th} to 21^{th} and Week_4 : December 24^{th} to 28^{th}. There are five weeks in July 2019 : Week_1 : July 1^{st} to 5^{th}, Week_2 : July 8^{th} to 12^{th}, Week_3 : July 15^{th} to 19^{th}, Week_4 : July 22^{nd} to 26^{th} and Week_5 : July 29^{th} to 31^{st}.

4. Once the week-wise ODpairs for each depot are obtained, the **same ODpairs** across four depots in the **same week** and in the **same time** interval(i.e.24 hours of the day are divided into 15 minutes) are combined.

5. From step no 4, one file for each week of December 2018 and July 2019 are output.

6. The passengers count of **same ODpair** across time intervals(i.e. every 15 mins) are summed up to get the total number of passengers for that ODpair in that week.

7. The ODpair file from step 6 got for each week is sorted in descending order according to the total number of passengers.

8. The sorted ODpair file is parsed to extract the top 100 ODpairs.

9. *The top* 100 *ODpairs from step* 8 *are analyzed for duration of peaks and the total number of tickets sold in the peak duration.*

Top 5 of the generated ODpairs for the 2 weeks of December are shown in table 3. From table 3, it can be observed that most of the ODpairs from Week 1 of December are occurring in other week of December as well. This informs that passenger movement across weeks remain similar. The next step is to examine the ticket sales in these top 100 ODpairs for the peak/off-peak times of ticket sales. The peak and off-peak times are identified using a Python script. Though in many of the routes, there are only 2 peaks(morning and evening peak) observed, in many other routes multiple peaks are observed. Also, since the maximum passenger count

Table 3: Top 5 ODpairs and their passenger counts, total ticket amount for 2 week in December 2018

From_bus_stop_id	From_stop _name	To_bus_stop_id	To_stop_name	Passenger_count	Total_ticket_amount
Week -1 : December 3^{rd} to 7^{th}					
134	Kundalahalli Gate	1629	Marathahalli	6401	32316
6930	AECS Layout Cross	2050	Sathya Sai Hospital	5341	74001
134	Kundalahalli Gate	154	NAL Manipal Hospital	4313	77013
2280	Hope Farm (Towards Varthuru)	140	White Field Post Office	4210	21143
7030	Bellanduru	2619	Marathahalli Bridge	4171	79290
Week - 2 December 10^{th} to 14^{th}					
134	Kundalahalli Gate	1629	Marathahalli	6346	32093
6930	AECS Layout Cross	2050	Sathya Sai Hospital	5285	73504
134	Kundalahalli Gate	8456	Kempegowda Bus Station	4439	113625
2280	Hope Farm (Towards Varthuru)	140	White Field Post Office	4233	21219
134	Kundalahalli Gate	154	NAL Manipal Hospital	4105	72389

between different ODpairs varies(as shown in figure 8), there is a need to systemically identify the peaks and off-peaks between different ODpairs. The steps of the algorithm to identify the peak and off-peak times of the day is given in 1.

Algorithm 1: Identification of peak time and duration

```
Data: Top 100 ODpairs data file, Weekdf = ODpair data file of a week
Result: ODpair, peaktime, peak_duration, number_of_passengers_in_peak_duration
Abbreviations: pxc = passenger_count;
foreach odpair ∈ top100odpairs do
    peak_pxc = Weekdf . max_passenger_count ;
    foreach row ∈ Weekdf do
        Iterate through the ODpair week data file containing passenger count in 15 mins time interval, to
          identify and retrieve all the time intervals at which the passenger count is atleast 70% of the
          peak_pxc.
    end
    Store for each ODpair = peaktime, peak_duration, no;of_passengers_in_peakduration ;
end
return ODpair, peaktime, peak_duration, no;of_passengers_in_peakduration;
```

The algorithm 1 is executed for four weeks ODpair data files of December and five weeks ODpair data files of July. The algorithm 1 provides 3 outputs for each week. They are for each ODpair, the peak passenger count, peak duration, time at which peak occurred. Additionally, the total travel time for every ODpair is computed in every week. Using these outputs the following two ratios are computed for every ODpair for every week.

$$peak\_pxc\_ratio = \frac{Average\_weekly\_peak\_passenger\_count}{Average\_weekly\_passenger\_count} \tag{2}$$

$$peak\_time\_ratio = \frac{Total\_peak\_duration\_of\_week}{Total\_travel\_time\_of\_week} \tag{3}$$

The week 4 of December 24^{th} to 28^{th} being a holiday week and Week 5 of July 29^{th} to 31^{st} having only 3 days are ignored for peak behaviour analysis. The sample output of peak_pxc_ratio for 10 ODpairs for all the weeks considered for analysis in December 2018 and July 2019 are shown in table 4. From the table 4 the following observations can be made.

1. The percentage of ticket sales in these ODpairs across weeks in both months are similar.

2. The variance in the peak ticket sales percentage is also less than or equal to 5%.

The travel time was then computed to examine the duration for which these peak ticket sales occurred. The peak_time_ratio as in eqn:3 was computed. The peak_time_ratio across weeks also remains similar. They are as shown in table 5. These peak time ratio are very low indicating that the time for which the peak occurs is very small. This behaviour was observed across weeks in both the months. This also is an evidence that the peak ticket sales are really high compared to the off-peak ticket sales. The top 10 ODpairs for which the peak ticket sales was observed is presented in table 6.

5 Discussion

The Table 6 shows that more than 30% of ticket sales occurs in the peak times. The ticket sales in some of the ODpairs goes as high as 60%. The column **Mean** under **peak_pxc_ratio** shows the mean of peak_pxc_ratio of 7 weeks(3 weeks in December and 4 weeks in July). Similarly the **Mean** under **peak_time_ratio** shows the mean of peak_time_ratio of 7 weeks. The peak duration are very less compared to the total trips time. This behaviour needs to be considered while scheduling. Jara Díaz et al [Ser17] have provided an analytical explanation that in urban cities − the number of buses and vehicle size is determined by the characteristics of demand during peak period and adjusting frequencies for other off-peak period whose characteristics are very different from that of the peak duration. They have shown numerically that minimizing social costs(operator and user) for the whole day results in a larger fleet of smaller size buses than if only peak period is considered for determining the fleet size and capacity.

Table 4: Sample Computed peak_pxc_ratio for some ODpairs

odpair_id	odpair_stopnames	December 2018			July 2019			
		peak_pxc_ratio(as in eqn:2)						
		W1	W2	W3	W1	W2	W3	W4
134_1629	Kundalahalli Gate_Marathahalli	0.10	0.11	0.11	0.17	0.12	0.12	0.13
6930_2050	AECS Layout Cross_Sathya Sai Hospital	0.23	0.26	0.24	0.27	0.22	0.23	0.26
7030_2619	Bellanduru_Marathahalli Bridge	0.22	0.23	0.26	0.30	0.29	0.29	0.30
2280_140	Hope Farm (Towards Varthuru)_White Field Post Office	0.15	0.13	0.13	0.15	0.17	0.13	0.14
1218_1234	Sony World 80ft Road Koramangala_Dhoopanahalli	0.23	0.23	0.27	0.28	0.24	0.18	0.22

Table 5: Sample Computed pxc_time_ratio for some ODpairs

odpair_id	**odpair_stopnames**	**December 2018**			**July 2019**			
		peak_time_ratio(as in eqn:3)						
		W1	**W2**	**W3**	**W1**	**W2**	**W3**	**W4**
134_1629	Kundalahalli Gate_Marathahalli	0.0404	0.0577	0.0361	0.0069	0.0299	0.0257	0.0201
6930_2050	AECS Layout Cross_Sathya Sai Hospital	0.029	0.0193	0.0229	0.0194	0.0323	0.0301	0.0128
7030_2619	Bellanduru_Marathahalli Bridge	0.0307	0.0168	0.0064	0.0148	0.0148	0.0148	0.0174
2280_140	Hope Farm (Towards Varthuru)	0.0166	0.0161	0.0377	0.0371	0.0163	0.0366	0.0163
1218_1234	Sony World 80ft Road Koramangala_Dhoopanahalli	0.0228	0.0058	0.0058	0.0056	0.0056	0.0232	0.0114

Table 6: Top 10 bus stops with high peak_pxc_ratio in peak time and the variance in peak time is very small

odpair_id	**odpair_stopnames**	**December 2018**		**July 2019**	
		peak_pxc_ratio		**peak_time_ratio**	
		Mean	Variance	Mean	Variance
2092_6914	Kadugodi Bus Station_Pattandur Agrahara Gate	**0.66**	0.0277	0.0014	0.00001
2092_140	Kadugodi Bus Station_White Field Post Office	0.46	0.0127	0.0029	0.00002
9010_9288	Police Station Indiranagara_Military Bridge	0.43	0.0104	0.0057	0.00002
2092_154	Kadugodi Bus Station_NAL Manipal Hospital	0.42	0.0068	0.0057	0.00002
2619_2581	Marathahalli Bridge_Dodda Nekkundi (Towards Hebbala)	0.39	0.0055	0.0043	0.00002
5557_2595	Kadabisanahalli _Bellanduru City Light Appartment	0.33	0.0064	0.0043	0.00002
7030_5228	Bellanduru _Kadabisanahalli	0.32	0.008	0.0057	0.00002
403_6919	Pattandur Agrahara Gate_Hope Farm (Towards Hoskote)	0.32	0.0081	0.0014	0.00001
2055_6929	White Field TTMC (Vydehi Hospital)_AECS Layout Cross	0.31	0.0024	0.0114	0.00007
134_2595	Kundalahalli Gate_Bellanduru City Light Appartment	0.31	0.0009	0.01	0.00006

The analysis tasks based on the ticket sales data as shown in this paper also show that the peak behaviour is very different from the off-peaks in the system. Hence, the process of planning and scheduling needs to consider both the peak and the off-peaks in the urban transit system.

6 Conclusion

The use of automatic data collection techniques various advantages. This study investigates the potential of ETM data and in general ticket sales data for the purposes of operations and planning. The ticket sales data can provide insights into quantitative measures for operational performance. This paper has shown a methodology for generating ODmatrices from ticket sales data along with various other analytical tasks. This paper also shows the effectiveness of ticket sales data for understanding various important performance indicators of the public transit agency. Future works involve coming up with schedule modelling based on Jara Díaz study.

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