# Estimating Link Volume Count Using Wi-Fi Scanners: A Case Study for Urban Road Network

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## Abstract

With increased mobility in metro cities, traffic congestion has become a prominent issue. Traffic control strategies involve network management techniques which requires several inputs such as travel times, link flow and turning movement. Traditionally, loop detectors are used to obtain link volumes on the network. The loop detectors provide suitable counts on homogeneous conditions but are proved to be inefficient for the heterogeneous traffic conditions. Considering these issues and with availability of latest Intelligent Transport Systems (ITS), this paper explores the possibility of using Bluetooth/Wi-Fi data in exploring link volumes. The paper highlights the challenges of the BMS data and correspondingly proposed a framework to estimate the links, considering the stated challenges. The adopted approach is test on two links for a Chennai city network in India and provides results with a MAPE of 15 to 18% for the congested hours and less than 12% for off-peak hours.

***Keywords— Link volume, WMS, Travel time, Occupancy***

## 1. INTRODUCTION AND LITERATURE REVIEW

There is a surging need to examine the performance of road networks under altered traffic conditions. Traditionally, the road performance is quantified by measuring traffic congestion on the network links. In literature, travel time-based measures such as average speed, Buffer Time index (BTI), Travel time index (TTI), and percentile speeds quantify the traffic congestions. Traffic controller agencies then attempt to reduce the overall network congestion by regulating the flow on the network. Traffic control strategies involve handling traffic signals, providing traffic information to travelers using Advanced Traveler Information systems (ATIS), congestion pricing, and other suitable techniques. These control measures require information such as travel demand, traffic flow/link flow and turning proportions in addition to the congestion indices. This information is currently available from in-road traffic measurement systems such as loop detectors, and magnetometers. These systems provide accurate data for homogeneous traffic conditions but also pose severe challenges concerning the installation cost, maintenance cost, and operation management. Besides, the devices possess several malfunctions leading to sporadic data gaps(El Esawey, Mosa, Nasr, & Systems, 2015) and are

inefficient in developing countries due to the high demand and heterogeneous traffic conditions(Ali, George, Vanajakshi, & Venkatraman, 2012).

Considering the above issues, modern Intelligent Transport systems (ITS) include several passive measuring devices such as GPS, Call Data Record (CDR), RFID scanners, Automatic number plate recognition (ANPR), Bluetooth, and Wi-Fi scanners. Passive sensing devices are cost-efficient, accurate, require less maintenance, and provide continuous data without any significant missing gaps(Tubaishat, Zhuang, Qi, & Shang, 2009). However, not all of these techniques are useful for the same purpose as each source provides the information with different accuracy and datatype. For example, GPS data provides the location update for the device at a particular time interval frequency. A higher frequency misses' information of the link traveled, whereas a low-frequency interval creates the issue of data storage. Further, it's hard to extract GPS data for each vehicle, and hence the technique is not used for extracting link volumes on the road network. Hence, the GPS data are useful for evaluating route choice behavior and path choices modelling but not for the link volume estimates(Casello & Usyukov, 2014).

RFID scanners are the alternatives of the GPS data, where the RFID scanners detect the vehicle if the vehicle equipped with the RFID is in the scanner's scanning range, then its information is stored(Blessingson & Jinila, 2010). However, the RFID scanner range is low and requires several scanners to be placed on the network to extract link volume information. Currently, the RFID scanner are used only for the public transport systems. Similarly, the ANPR scanners require advanced video-based image processing techniques and high computational and processing techniques to extract meaningful information(Mallikarjuna, Phanindra, & Rao, 2009). Also, the ANPR sensors needs to be placed at all approach and midblock in the network, which is cost expensive. CDR and Bluetooth/ Wi-Fi scanners possess a similar process of vehicle identification. CDR data is obtained from the phone tower stations, which provide information on the individual phone data within its coverage zone(Mouchili, Atwood, & Aljawarneh, 2019). The towers' scanning range is significantly more extensive and ranges from few meters to few kilometers depending upon the towers' density. As the scanning range is higher, it is difficult to trace the vehicle within its scanning zone. Only one study has attempted to use the CDR data to extract the link volume for a smaller network and addresses the issue of overlapping zone in estimation the link volumes(Caceres, Romero, Benitez, & Castillo, 2012). Thus, the CDR data can extract travel patterns or estimate flow within zones but are incapable of estimating the link volumes.

Bluetooth Mac Scanners (BMS) and Wi-Fi Mac scanners (WMS) possess a similar vehicle identification structure as the CDR data. However, the two differ based on the scanning zone radius. BMS/WMS data is extensively used to estimate travel time(Chintan Advani, Thakkar, Shah, Arkatkar, & Bhaskar, 2019b; A. Bhaskar, Qu, & Chung, 2015), OD matrix(Chintan Advani, Thakkar, Arkatkar, & Bhaskar, 2020; Bianco, Confessore, & Reverberi, 2001), trajectory estimation(C. Advani, Bhaskar, Haque, & Cholette, 2021; Michau et al., 2017) , performance evaluation (Chintan Advani, Thakkar, Shah, Arkatkar, & Bhaskar, 2019a) ,and understanding human travel patterns(Abedi, Bhaskar, & Chung, 2014). WMS possesses a shorter scanning radius, ranging from almost 150 to 200 meters depending on the antenna strength(Abedi, Bhaskar, Chung, & Miska, 2015). The scanners capture the vehicles' mac-id if their wi-fi/ Bluetooth is switched on and is within the BMS scanners' scanning zone. Interested readers can refer to (Ashish Bhaskar & Chung, 2013) for further understanding of the Bluetooth scanners. Note: The problem of the overlapping scanning zone in the link volume estimation is

out of the scope of this study as the link considered in this study are suitably apart and the BMS/WMS possess suitable smaller scanning radius. These scanners are placed either at intersections or the midblock sections, depending on the study's purpose(Hainen et al., 2011). Thus, a vehicles' MAC id is traced at several locations on the road network, which helps provide the travel information.

While the Bluetooth data has been extensively used to estimate travel time, travel patterns, OD matrix, and vehicle trajectories. To the best of the authors' knowledge, no studies exist that have explored the passive sensing device such as BMS/WMS to obtain link/ section flows on the road network. This study provides a practical alternative to loop detectors that can be used to estimate accurate link volumes, especially for heterogeneous traffic conditions. This study attempts to use the Bluetooth/ Wi-Fi data to estimate the road sections' vehicular flow.

## 2. RESEARCH PROBLEM

As stated above, Bluetooth / Wi-Fi MAC id is traced at several BMS placed either at the intersection or on the midblock section. A vehicle is considered to be traveled on the link if it's simultaneously detected at both the adjacent scanner. To understand it better, consider the Fig.1below:


Figure 1 Process of tracing BMS id from scanners

In the above figure, the scanners are located at points L1 and L2 placed 1.2 km apart. Each scanner provides the information of the vehicles MAC and its corresponding timestamp of detection. A vehicle is considered to travel on link L1-L2 if it was first detected by scanner at L1 and followed by a successive detection at L2. Note: The link volumes are directional based, the flow $L_1$-$L_2$ is not similar to flow $L_2$-$L_1$.

Loop detector data possess the following key issues for link flow estimation:

1. The loop detectors under-estimates the flow due to the presence of 2/3wheel vehicles in the heterogeneous traffic conditions
2. The loop detectors are placed at the approach of the intersections/ roundabout. This provides the information only on the vehicles approaching the intersection.

3. As shown in Fig.1, several minor street entries and exit links exist between the link $L_1$-$L_2$. Information regarding the through traverse ( complete travel on $L_1L_2$) cannot be obtained from the loop data.

The issues from the loop detector data can be resolved using the implementation of the BMS data. However, the problem is wicked as the Bluetooth data possesses its own challenges such as:

1. Bluetooth scanners cannot identify the type of device, i.e., heuristics are essential to filter static and non- vehicle devices (**Issue 1**)
2. The penetration rate varies based on the traffic demand, and a fixed penetration rate does not exist (**Issue 2**)
3. The penetration rate (ratio of observed to actual flow) is lower for these scanners (**Issue 3**)
4. The BMS scanners cannot identify vehicles with multiple devices, which tends to overestimate the vehicle flow using existing scaling techniques (**Issue 4**)

Corresponding, the link volume extraction requires a strategic framework that estimates the flow with minimum errors. This paper proposes a framework to address the above challenges by estimating the flow using the Bluetooth data. Note: In literature, a link is defined as the section connecting two intersection. This is because the scanners and the measuring devices are usually placed at the approach of the intersection. However, for the current study, link can either be a connection between two intersection, two midblock points or among an intersection and a midblock point.

The above definition of the link is adopted, to generalise the applicability of our method. This helps to apply the proposed technique not just for estimating flow between two intersection but can be applied to problems such as quantifying the bottleneck effect, analysis the effect of incident on the network and for generating empirical fundamental diagram.

The paper's remainder is categorized as follows: Section 3 of the paper discusses the data collection process describing the study sections followed by the overall framework's expression in section 4. Section 5 provides a detailed understanding of the various elements stated in the methodology, and lastly, the inference and conclusion of the paper are expressed in section 6.

## 3. DATA COLLECTION

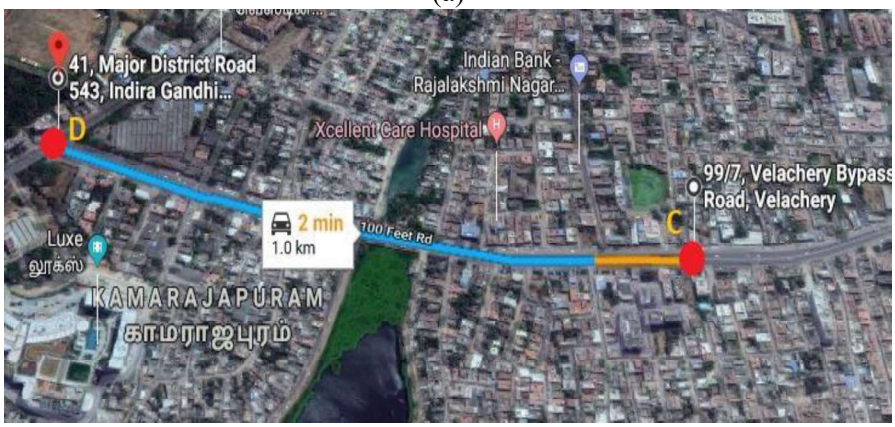
This study considers two links on a Chennai network to develop and validate the proposed framework. As stated earlier, a link is defined as the path connecting the two WMS as shown in the figure 2 and hence 4 WMS were used in this study. The links were identified such that multiple congestion levels can be observed throughout the day. The paper proposes that the links should be established between an intersection and any point in midblock. Although the proposed network link establishment is unlikely to the general graph, it possesses several advantages with ease in data processing and accuracy of the estimated link volumes. In any case, the method is generalised, and can be implemented for any links.

Due to the unavailability of loop detectors, the actual flow (both directions) was extracted manually from video cameras installed at the intersections for both the links. The selected study links are on a different path with no interdependency. Considering that the Bluetooth/ Wi-Fi scanners possess a large detection range (150-300 meters) (Abedi, Bhaskar, & Chung, 2013), scanners were placed at least 1 kilometre apart to have an appropriate clear distance between

them. Note: A clear distance is defined as the distance from the exit of the upstream scanners to the entry of the downstream scanner.

Figures 2 (a) and 1(b) show two links: A-B and C-D of the Chennai city network, considered for estimation of link volume. The link A-B is 1.7 kilometres long and six-lane divided with an additional service lane on both the side of the road. Whereas the link C-D is 1.5 km long and is four-lane divided with an additional service lane running throughout the stretch in both directions. The sensor at A is placed near the median of a Foot over the bridge at the height of 16 feet. Whereas the sensors at points B and D are placed at the intersection where the video-based volume count cannot be determined. The sensor at C is placed at the median of the road, on the lamp post at a suitable height of around 6" to capture suitable ids for all the vehicles moving over the link as suggested in the literature(Brennan Jr et al., 2010).


(a)




(b)

Figure 2: Data collection for (a) Link A-B (b) Link C-D

Consequently, for both the segments, similar traffic conditions were observed to prevail across the examination duration. Likewise, both the links are a part of the IT corridor in Chennai city, which extends the pertinence of results from one link over the other. Based on past literature, an antenna with a gain of 5dbi was deemed appropriate for collecting data. The antennas were polarized vertically to enhance data collection efficiency(Porter, Kim, Magaña, Poocharoen, & Arriaga, 2013). The data from the sensors and the video cameras were collected on two days, including a weekday and a weekend, to capture variations in traffic volumes.

## 4. METHODOLOGY

Section 2 stated the link flow estimation challenges using the BMS data. The proposed framework is Fig 2 shows the sequential procedure of addressing the stated challenges. The flowchart consists of specific blocks, each focusing on one aspect of the problem.

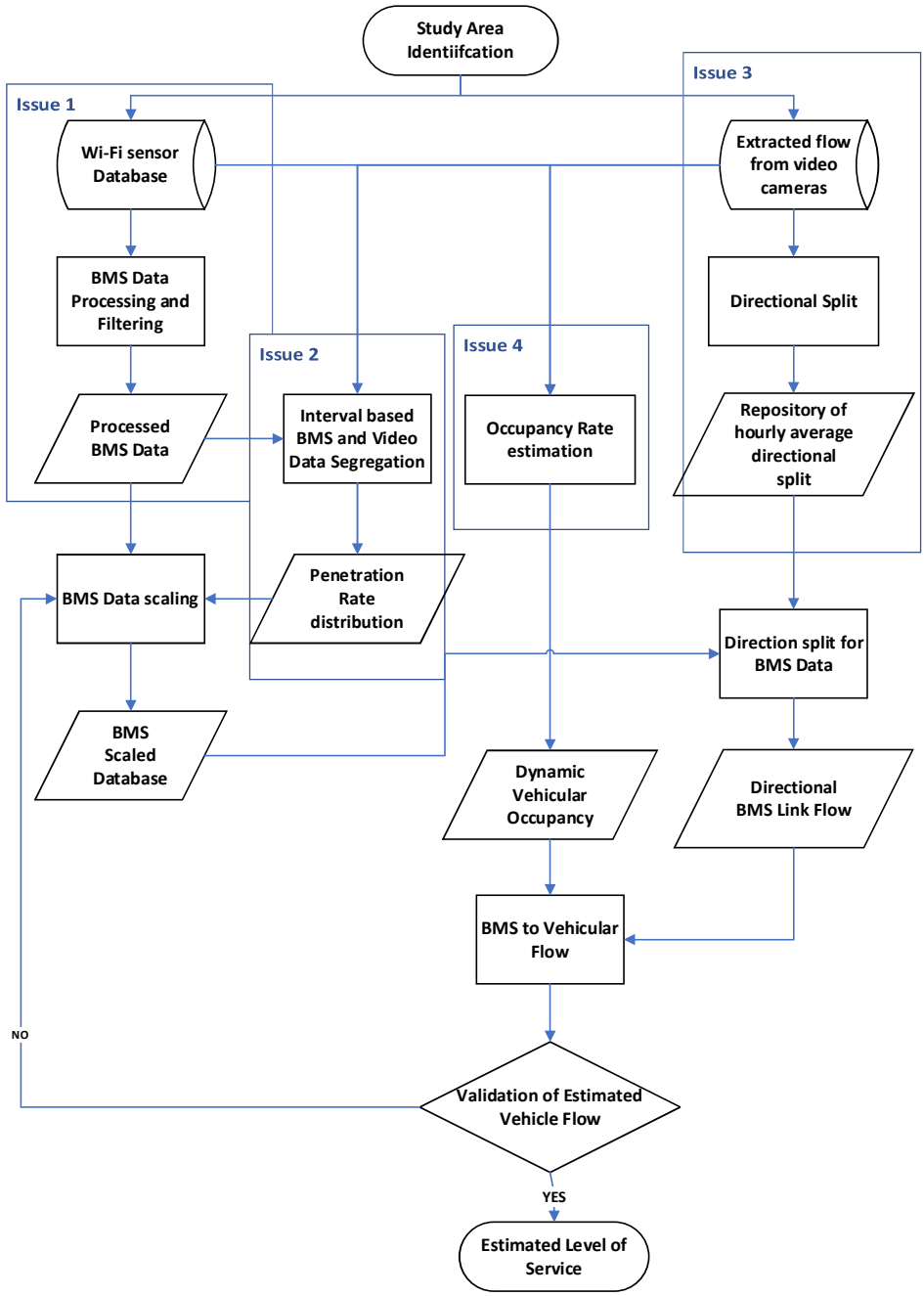



Figure 3: Methodology adopted for estimation of link volumes.

The entire framework can be categorized into four major sections:

- **Data cleaning and filtering by removal of non-essential ids:** This section explains the procedure of identifying static ids and non-vehicular ids based on the travel time constraints.
- **Estimating the penetration rate and scaling the WMS data:** This section explains the process of dynamic penetration rate estimation and its application in scaling the WMS data.
- **Converting scaled WMS data to directional link flows:** This study requires the directional link flow estimation process. This section provides the process of finding directional proportions, thereby providing statistical comparison to evaluate the confidence of directional flow estimates.
- **Obtaining vehicular flow from directional link flow:** Lastly, the scaled WMS data consists of the scaled scanner ids. As the vehicles can possess more than one device, this section provides the descaling process of converting ids to vehicular flow.

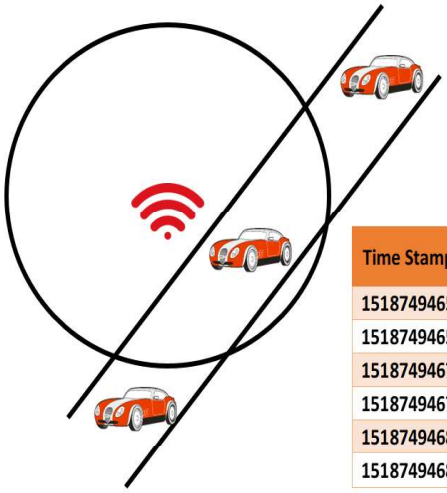
The following sections describe each component individually in detail, where the first step of data cleaning and filtering is like the methods adopted in the literature. The processed WMS data and the video count were then segregated into 15-minute time intervals for the entire study period. The segregated data distributes the varying penetration rate obtained from 15 minutes segregated WMS detection data and the observed traffic volume. This step is essential to develop a repository of the observed penetration rate distribution, which is further used for WMS link flow estimation. The scaled WMS flows are then split into directional link flows by applying a split factor, determined based on the observed counts. Lastly, the occupancy estimation process is used to obtained vehicular flow from the WMS link flows.

## 5. Staged Process of Link Volume Estimation

This section explains the four staged procedures for estimating the link volume as stated in the methodology section.

### 5.1 Data filtering and cleaning

A two-step filtering processing is adopted to remove the unessential ids such as static devices, cyclists, and pedestrians. The first stage of filtering identifies the time duration for which the ids were observed at the same scanners. The difference in this time, which indicates travel time to cover the detection range, helps categorize the type of traveller moving on the road i.e., pedestrians, cyclists, and vehicles. As the sensor is placed at the unsignalized point in the midblock, the considering of signal timing is nonessential in the data processing process. An example of the retrieved data retrieval process and its initial processing is stated in Fig.3.



| Time Stamp | Wi-Fi MAC Id | Signal Strength | Location Id | Data Cleaning |
|---|---|---|---|---|
| **1518749465** | da:a1:19:05:9a:95 | -58 | 265831 | Accepted |
| **1518749465** | da:a1:19:05:9a:95 | -63 | 265831 | Rejected |
| **1518749467** | da:a1:19:df:0f:a6 | -63 | 265831 | Accepted |
| **1518749467** | da:a1:19:df:0f:a6 | -65 | 265831 | Rejected |
| **1518749468** | ac:c3:3a:30:2a:1a | -53 | 265831 | Accepted |
| **1518749468** | 5c:99:60:0e:1e:96 | -64 | 265831 | Accepted |

Figure 4: Removal of duplicates from dataset

In the above process, all the multiple detections are removed, keeping only the first timestamp of detection. The data cleaning is essential as the consideration of all unique ids without any processing will incorporate devices (e.g., pedestrians, static devices) that may induce significant noise and error in link volume estimation.

Following this, the second stage of filtering involves removing ids that were observed at both ends of the link. The MAD filter (Ashish Bhaskar, Qu, & Chung, 2014) was adopted for similar reasons to remove the unessential ids. Finally, to test the filtered result's effectiveness, the correlation coefficients were observed between WMS ids and observed counts. Before the processing, the correlation value was observed to be 0.22, which increased to 0.47 after the above two-stage filtering process.

### 5.2 Scaling the processed WMS ids to WMS volume

Usual practices involve the scaling process of WMS ids observed at both ends (nodes/scanners) of the link. The scaling process requires the scaling factor, which is the inverse of the link average penetration rate. Here the link penetration rate can be defined as:

Link Penetration Rate = Matched WMS id at the scanners / Flow on the link

There are two issues with the above existing scaling process,

1. Bluetooth and Wi-Fi devices tend to have missed observation, leading to an observation missed at either of the scanner (Michau et al., 2017).
2. Some devices might have escaped/ added on the links, which cannot be identified as it is impossible to know the actual flow on the link based on loops.

Moreover, these techniques yield less efficiency with less than 1% of the total flow matchings. Consequently, this study adopts point-based filtering [section 5.1] and scaling process.

A point-based penetration rate (i.e., penetration rate from a single scanner) is estimated and applied for this study, where the penetration rate is the ratio of observed mac its id to the actual flow passing through the scanner. The penetration rate will vary with changes in volume passing through the scanning zone. Therefore, the penetration rate is calculated at various observed

volumes, and a database indicating the range of variation (penetration rate) was determined. Note: The penetration rate study was conducted for the scanner established at the midblock. This is because the scanner placed at the intersection would require volume from all links, which is time-consuming and will induce more errors.

The inverse of the observed penetration rate indicates the expansion factor(Blogg, Semler, Hingorani, & Troutbeck, 2010). The point specific expansion factor is multiplied with the ids acquired after the initial processing, as explained in section A. This determines the total WMS ids passing through the scanner, and it includes the vehicular movement in both directions. This gives an idea of the real WMS ids moving over the link (both ways). Results show that a relation exists between real captured unique ids and the penetration rate. In this study, a range of the penetration rate was determined for various traffic volumes. For a given range of traffic volume, the observed penetration rate is assumed to follow a normal distribution. Using the monte Carlo simulation process, random values of penetration rate were extracted using 50 random draws and the average value of these distribution is considered for the scaling factor. Using the above technique, a penetration range was observed ranging from 0.2 to 0.3 depending upon the traffic volume, which leads to a scaling factor of 3.5 to 5.

Thus, for a given WMS volume, an averaged penetration rate is known using the Monte Carlo approach. This volume-dependent penetration rate is then considered for estimating the scaling factor. For instance, considering that a WMS volume of 1700 ids is observed at various intervals, a penetration rate of 10,30,20,25,15 correspondingly. The above penetration rates are assumed to be a part of normal distribution and a which leads to an average rate of 20% after generating 30 random draws. Thus, for scaling the BMS ids, a scaling factor of 5(100/20) should be considered. This method's advantage is the existing process of static threshold for scaling in not violated but instead is based on the average rates, which helps not overfit the data. It should be noted that similar average rates are calculated for different volumes, and as the detection volume of total unique ids varies, the penetration rate will be modified. These expanded ids obtained from scaling the observed WMS volumes will then represent the total devices moving from that point (scanner) in either of direction. However, until this point of time the direction of the devices passing through the scanner is unknown. To gain this information, it is necessary to split these expanded ids based on the trips' directional movement, which is explained in the third step.

### 5.1 Splitting the WMS volume

WMS captures ids in either direction of movement. In the past, attempts have been made to use signal strength to understand the directional movement, but it only reveals the distance from the scanner and not the direction of the movement. The directional split can be estimated from the observed link count, but a convenient and appropriate way is by determining the matching trips in both directions. This way, a directional split can be resolved, and the ids should be split in the proportion obtained in both the direction.

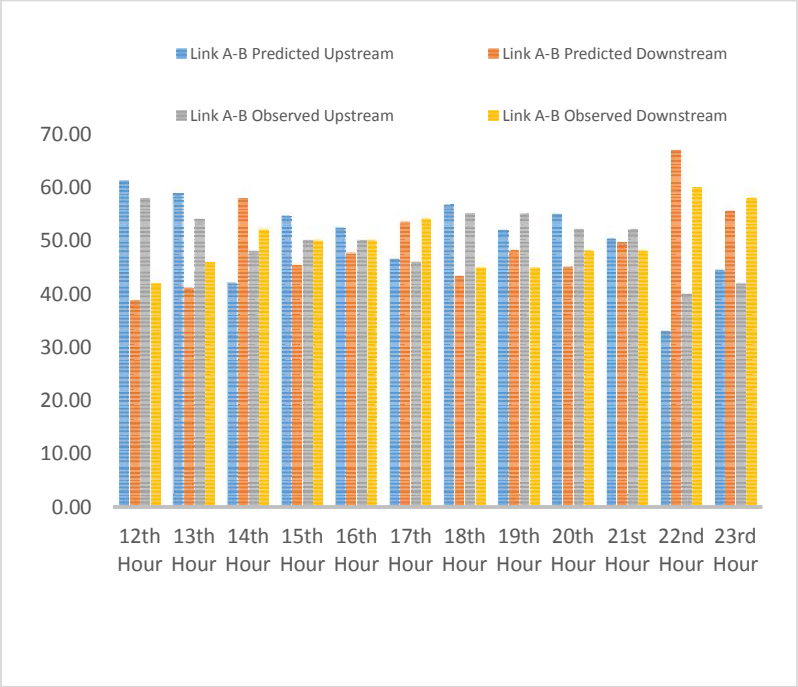



Figure 5: Directional split in upstream and downstream direction for link A-B

Figure 5 shows the directional split for the link obtained from the actual volume extracted from a video. It can be inferred that the directional split varied from 40% to 60% for all the hours of the day. It is observed that the flow in the upstream direction is relatively higher than the downstream flow for both the links. The chart shows the directional split observed from the sensors and its comparison with the observed distribution obtained from the video extraction. The results yield a significant correlation among the two distributions for all hours of the day. This signifies that the WMS ids can capture the direction movement pattern to a larger extend. To conclude this hypothesis, an attempt was made to check if a correlation exists between the estimated directional WMS flow and the observed unique ids in a particular direction.

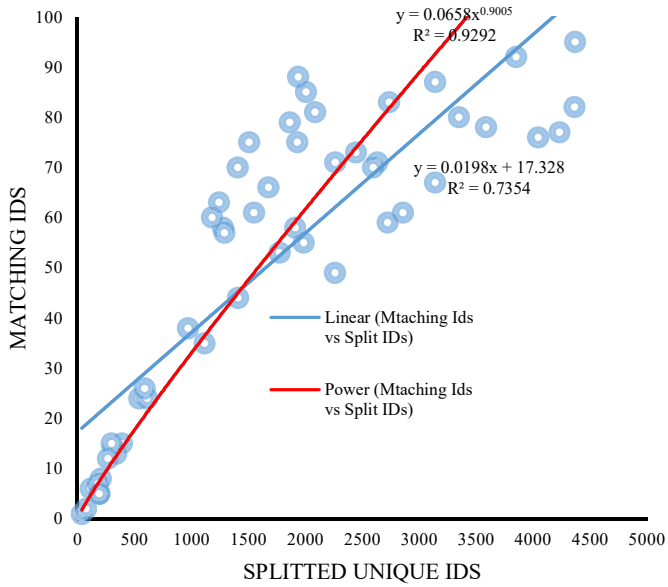



Figure 6: Linear and Power Distribution between Matching and Split ids

The data points in Figure 6 shows the correlation between the unique directional ids vs. the matching ids. It should be noted that for the directional ids, the data set consists of the ids moving in both upstream and downstream direction. Later, the matching WMS ids in their respective direction are plotted. The dataset of two days is included here and aggregated at an hourly interval to increase the data points for consideration at all volume levels. The low volume is observed for the night duration and higher volumes are for morning and evening hours.

In this context, we are looking for a comparison where the $R^2$ value is higher. For this, two types of distributions are plotted here; the first one is linear (blue), whereas the second is a power function (red). Here, the power distribution shows the most reliable data fit for the existing data set with a significantly higher $R^2$ value. However, the reliable fit of a linear distribution makes it easy to interpret the correlation among the variables, and also, the applicability of the method becomes easy for any generalized network. Hence, it can be said that either of the two distributions can be considered for establishing a relation between the separated id based on matching detections. The approach for filtering the cut-through traffic, which is considered for bifurcation, is expressed in the next section.

### 5.2 Determining vehicular flow

As it is known by now that the major limitation with the sensor is that it cannot categorize the type of vehicles as well the occupancy of the vehicle is not directly known (Ashish Bhaskar & Chung, 2013) and is iterated by indirect measures. This is one of the most important and challenging steps for the estimation of link volume. The conversion of link volume to traffic count is only possible when the vehicles' accurate occupancy is known. To this end, the method proposed by [20] is considered to identify the average occupancy values. The identified occupancy factors are considered to descale the directional BMS volume estimated in the above stage to predict the directional vehicle volumes that might exist. The predicted vehicle volumes are thus the estimated link volumes on our network. Table 1 shows the predicted link volumes in either direction of the node for the link A-B. A similar procedure was adopted for the link C-

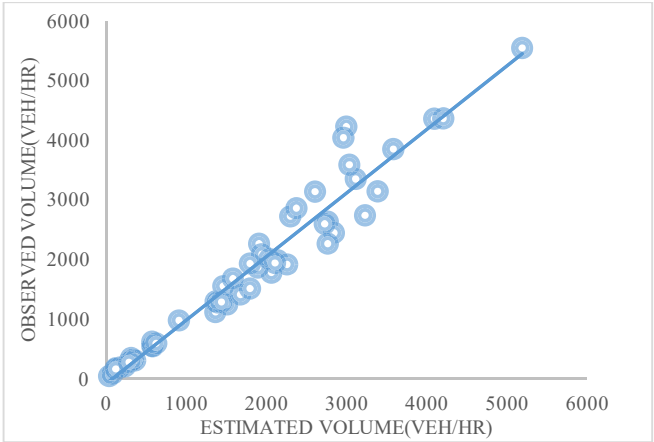
D, and the estimated volumes of both the links are then used in the following sections to validate the results.

Table 1: Predicted Link volume in both directions

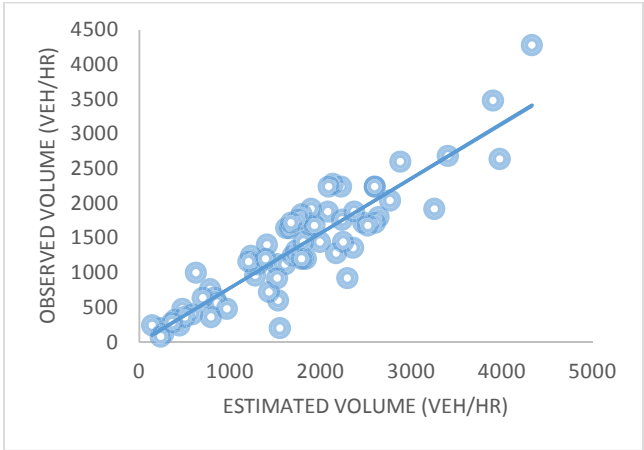
| Hour of the day | Link volume in the upstream direction (Veh/h) | Link volume in the downstream direction (Veh/h) |
|---|---|---|
| 12 | 3140 | 2118 |
| 13 | 2737 | 2315 |
| 14 | 2775 | 2445 |
| 15 | 2721 | 3260 |
| 16 | 3139 | 3858 |
| 17 | 3347 | 5286 |
| 18 | 5547 | 4229 |
| 19 | 4361 | 4042 |
| 20 | 4366 | 3585 |
| 21 | 2633 | 2596 |
| 22 | 1116 | 2264 |

### 5.3 Method Validation

The last stage of the process is the validation, i.e., comparing the observed data with the predicted data as shown in Figure 7(a) and 7(b). In the figure, each data point indicates volume corresponding to each hour. The data points obtained from the entire study period were considered for establishing the co-relation. This helps to check the discrepancy among dataset all volume levels. It is interesting to note that for all volume levels, the penetration rate varied among a constant range between 0.22 to 0.28. Hence, for most cases, the mean of the above range of 0.25, was considered as a penetration value. The present study can also be carried forward in understanding the accuracy of forecast considering a static penetration rate.




(a)




(b)

Figure 7: Co-Relation between observed and predicted volume for (a) Link A-B (b) Link C-D

Figure 7 shows that a significant correlation is observed between the observed and estimated volume for both the study link based on the paper's procedure. However, some dispersion is observed in higher volume flows, whereas it is relatively less for lower volumes. Thus, the influence of heteroscedasticity is observed with varying traffic volumes, indicating higher accuracy in the case of intermediate and low volume flow. The MAPE observed between the observed and the estimated volume is estimated around 12 to 18% for both the links and for most hours of the day, which is significantly good among the various methods considered traditionally. The MAPE of 18.2% was observed for the link A-B in the peak hour traffic whereas MAPE for the link C-D was observed to be 15.56%. Further, for the off-peak hours the MAPE of 14.6 and 12.3% was observed for link A-B and C-D respectively. The results suggests that the errors are sensitive to the actual volume and accordingly the method is reliable for low to moderate volumes but requires further improvement for high volume estimates.

## 6 Summary and Conclusion

The study provides the stepwise procedure for estimating link volume on two different links with different placement conditions of sensors in the network. The study explains the role of different parameters affecting the link volume. The study begins with the two-step cleaning and filtering to segregate vehicular ids from the total ids. The data cleaning is followed by the expansion of the total obtained unique into the possible link unique ids without considering the effect of occupancy or vehicle proportion. The expansion factor's effect is determined by previous literature studies expressing the variation of the expansion factor concerning the penetration rate. By studying the above parameters and applying relevant distribution factors, the directional expanded unique ids were determined. The explanation for the bifurcation of the unique id on both the links is different as the field conditions are dissimilar. The reliability of the bifurcation of the unique ids is also expressed in various plots and significant reliability is observed for all the study sections. Thus, after the dynamic occupancy rate applications for the obtained expanded directional volume, these ids were reduced to express the total vehicle moving on the link for both directions.

The results showed that the prediction of link volume was more accurate during lesser congestion levels. However, in peak hours when higher congestion exists, the assessment was nearly the same. The estimated directional volume was also compared with the field conditions,

and the results indicated that the study is prominently accurate in predicting the directional split. Thus, based on all the above parameters, the study approach is satisfactorily decent and can be used for the field conditions when the availability of sensors is scarce and economical. Besides, the MAPE value observed for both the links is considerably within the optimum limits, which indicates that the volume forecasting is reliably efficient for all traffic link conditions. However, the accuracy of the results can always be improved if the network is closely packed with a greater number of sensors and fewer escapes and altered methods for validation of the results.

The general perception is that Bluetooth/Wi-Fi technology could reliably estimate link volumes with a high level of precision, which can come about into its convenience in numerous field applications. Then again, the use of Wi-Fi, which can help get a comparable database, was seen to be one of the less-investigated advancements in this area. It is additionally noteworthy that, even though Bluetooth is picking up prevalence in India as an information-gathering strategy due to its cost-viability and simplicity of establishment, contemplates relating to this region were not generally seen in Indian conditions. In this manner, the utilization of Wi-Fi-based sensors for information gathering in Indian conditions can be considered as another technique supplanting conventional innovations having extensively less example size and exactness. Similarly, the paper's outcomes can be used for further determination of route choice studies and Origin-Destination matrix estimations, which will be a necessary input for the development of planning strategies.

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