REAL TIME TRAFFIC ANALYSIS USING DECENTRALIZED SIOT

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Declaration

Thesis is submitted to the Department of Computer Science and Engineering, BRAC University, Dhaka by the authors for the purpose of obtaining the degree of Bachelor of Engineering in Computer Science and Engineering. We, hereby declare that this thesis is based on results we have found ourselves. Materials and resources taken from any research conducted by other researchers are mentioned in references. Our thesis either in whole or in part, has not been previously submitted for any degree.

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ABSTRACT

The traffic is growing exponentially and expected to be more congested by thousands of millions of vehicles in near future and will become an inescapable problem across the world. It will certainly be troublesome to communicate, navigate and finding desired services within this huge and congested traffic domain. It is highly necessary to find best routes in the congested traffic domain in order to minimize the hours wasted on the streets. Existing centralized system to maintain this traffic domain will minimize the outcome in terms of cost, time and scalability issue. By integrating social networking concepts into Internet of Things a new paradigm has been proposed named Social Internet of Things (SIoT). In this paper, the main focus is to design an efficient, dynamic and reliable decentralized system that integrates Social Internet of Things (SIoT) concept in the traffic domain in a distributive manner by assuming each vehicle as an IoT device. Unlike humans, vehicles will be guided artificially to create its very own society with various relationships within the network. The underneath concept is that every vehicle will communicate with other vehicles using it’s friendship in a decentralized manner, with only local information. In the network of smart IoT devices, by performing experiments on network properties and analyzing the result traffic congestion has been predicted.

Index Term: Social Internet of Things (SIoT), IoT device, Centralized, Decentralized, Distributive.

Acknowledgement

Idea of the innovative research came to the intellectual mind of Dr. Amitabha Chakrabarty, Assistant Professor of the School of Computer Science and Engineering of BRAC Univeristy. He thought the four of us-Sifatul Mostafi, Farzana Khan, Md Kamrul Islam Antar and A.K.M. Robinuzzaman are worthy to carry out this research successfully.

We would like to express our cordial thanks and utmost gratitude to our supervisor; Dr. Amitabha Chakrabarty, Assistant Professor and our co-supervisor Sir Dipankar Chaki, Lecturer of the School of Computer Science and Engineering of BRAC University for providing their valuable insight, suggestion and guidance at our research. A continuous supervision, motivation and the spirit to push us more for getting a great thesis and an astonishing on this work would never be possible without them.

We would like to remember the contribution of Tasniya Ashrafi Heya, Research Assistant of BRAC University for assisting and guiding us.

We are thankful to Google map and Bing map services for providing us satellite view of traffic. Without those services we would not be able to collect data for our research.

Lastly, we convey gratitude from the depth of our hearts towards the faculty members of department of Computer Science and Engineering for providing us with all the knowledge throughout our undergraduate life so that we could do this research.

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CHAPTER 1

Introduction

In introduction, we will discuss our research work briefly and give a complete overview of our work. Our analysis and predicted solution are discussed in this chapter. Later, other parts of this report contain more information about our findings and analysis.

1.1 Introduction

Recently there has been a good number of researches investigate the potentialities of integrating social networking concepts into Internet of Things and attempts find solutions of several problems. The resulting paradigm named Social Internet of Things (SIoT) potentially supports novel applications and networking services for the IoT in more effective and efficient ways. According to [1], when a large number of individuals tied in a social network, it can provide far more accurate answers to complex problems than a single individual. That is why several proposals exploit use social networks to search internet resources, to route traffic, or to select effective for content distribution like [2], [3], [4], [5], [6] and [7].

The Internet of Things integrates a large number of technologies and envisions various smart objects [8]. According to this concept, objects can interact with each other and cooperate with their neighbors to accomplish common goals [9, 10]. The underneath idea of SIoT network is that every object will communicate with each other for searching their desired service by using its relationships, querying its friends and the friends of its friends in a distributed manner for an efficient and scalable discovery of objects and services by following characteristic principles of social networks for humans. The underneath principle of navigability of social network is based on the small-world phenomenon of the sociologist Stanely Miligram [11]. From Miligram's experiment, Kleinberg concluded that there are structural clues that help people to find a short path efficiently without a global knowledge of a network [12].

Traffic jam is a major problem in most cities around the world and it results in massive delays, increasing fuel wastage and monetary losses [13]. The losses occurring because of traffic congestion can be minimized if there is a way for shortest or best route selection. Based on the above mentioned idea, we have analyzed traffic network by assuming as a social network of Internet of things and stated prediction regarding traffic situation of a particular area. Like humans, a vehicle will query to its friends and the friends of its friends searching for its desired information in a decentralized manner using only its local information. Our prediction will acknowledge a vehicle regarding traffic situation of its destination by communicating with its friends by using local information.

1.2 Motivation

The main motivation behind this research was reducing the problem of traffic congestion by integrating the concept of Social Internet of Things (SIoT) in traffic network. Building traffic network and analyzing it was not very easy for us. We had to collect data from the scratch and build the network and by using this data the appropriate output prediction was very tough job. To make our research helpful for the sake of our country was the main motivation for us.

Our goal is to predict traffic situation so that a vehicle can choose the best route among alternative routes to reach its destination faster. In a research [14] we found that traffic jam causes loss of Tk 227 cr per month. If traffic jam can be reduced a bit then this huge amount of money and people's valuable time can be saved, their sufferings will be reduced and productivity will increase.

In our research, we have analyzed traffic network in order to predict the traffic situation. Our aim for predicting traffic network is to enable vehicles to reach their destination faster and reduce the losses occurred due to traffic jam.

1.3 Thesis Contribution

The objective of this thesis was to analysis of traffic data, to find out which vehicles are more responsible for creating traffic congestion and which network property has better effectiveness for choosing the best route for going from a particular source to the desired destination. The analysis can be used by other researchers who are willing to work on innovating ways for best route selection in decentralized approach. This thesis gives an insight of the network properties of the traffic network and what is their impact in traffic analysis. Even if the idea of Social Internet of Things (SIoT) has been already discussed, in this paper we go beyond the state of the art in several ways:

- We identify appropriate policies for the establishment and management of social relationships between vehicles in such a way that the resulting social network of vehicles is navigable.
- We study the characteristics of the SIoT network structure and present some interesting result obtained from traffic domain through software Gephi [23].

1.4 Problem Statement

There is no live traffic data available in Bangladesh. We attempted to collect live traffic data for research purpose but we could not find any source that provides live data. We therefore had to collect data from satellite view of Google Maps, Bing Maps and Yahoo Maps. By considering each vehicle as a node and distance between two vehicles as their connecting edge, we have prepared dataset in CSV (comma delimited) format. We collected traffic data only for Bijoy Sarani junction. Although the data was finally collected, it has some missing data. We may have missed some vehicles because all the vehicles are not visible in the satellite view. The data was filled by our visual assumption.

1.5 Solutions

We collected the same data from Google Maps, Bing Maps and Yahoo Maps to make dataset more accurate.

1.6 Methodology

We created traffic dataset from satellite view of Google Maps and Bing Maps. We considered traffic network as a social network of Internet of Things. The network we made from Google Maps is Dataset 01 which gives us traffic information of 2013, the network we made from Bing Maps is

Dataset 02 which provides us traffic information of 2017 and the network we made from Yahoo Maps is Dataset 03 which provides us traffic information of 2014. Then we simulated several network properties on our datasets, analyzed those and then made comparison between three datasets.

1.7 Data

For our research, there was no data available. That is why we to prepare our own dataset. We had collected traffic data from Google Maps, Bing Maps and Yahoo Maps satellite view and prepared a traffic network for our research purpose.

1.8 Thesis outline

- Chapter 1 gives a brief overview of our research, our estimated goal and what we have gained.
- Chapter 2 discusses the literature review and background study of our thesis, what properties we considered and how they work and more.
- Chapter 3 discusses about the chosen methodology, and the reasons behind choosing it.
- Chapter 4 discusses comparative study and analysis of the resulting output we found. The trial and error stages are also briefly discussed in this chapter.

- Chapter 5 ends our paper with conclusion and proposed future work for the system.

Chapter 2

Literature Review

The IoT is a world-wide network of interconnected objects uniquely addressable, based on standard communication protocols [15]. According to [16], the Internet of Things (IoT) integrates a large number of heterogeneous and pervasive objects and those objects continuously generate information about the physical world. IoT technologies provide new services to end users in disparate fields [16]. Social applications of the IoT have been evolving into a new novel paradigm of “social network of intelligent objects”, which is known as Social Internet of Things (SIoT) [17]. In [18] and [19], a first definition of the SIoT has been provided based on the notion of social relationships among objects. The SIoT is considered as a network where every node is an object capable of establishing social relationships with other objects in an autonomous way with respect to the rules set by the owner. From [17], we have found various types of social relationships in which things can be engaged such as parental object relationship, co-location object relationship, co-work object relationship, ownership object relationship and social object relationship. The parental object relationship is defined among similar objects built in the same period by the same manufacturer; this type of relationship does not change over time [8]. Co-location and co-work object relationships are determined whenever objects constantly reside in the same place or periodically cooperate to provide common IoT application [8]. These types of relationships change frequently and are dependent on the time duration of co-location/co-working and on the frequency of the interaction [17]. The ownership object relationship is defined for objects owned by the same user [8]. Finally, the social object relationship is established when objects come into contact, sporadically or continuously, for reasons related to relations among their owners [17].

We have studied social relationships among vehicles [17]:

- Vehicles produced by same producer and created in the same period of time can establish Parental Object relationship (POR). This type of relationship can provide useful information about the status of a vehicle.
- When vehicles come into contact sporadically or continuously because their owners go to work or come in touch with each other than Social Object Relationship (SOR) is established. The more often the vehicles meet, the stronger the relationship becomes and the

higher the value it provides regarding service discovery and trustworthiness evaluation [20], [21]. The benefits derived from SOR is very important for traffic scenario because vehicles related by SOR share useful information regarding traffic conditions or petrol stations. SOR takes account for common vehicle paths and locations.

- When vehicle meet continuously, they can establish Co-work Object Relationship (CWOR). These relationships can provide useful traffic information to guide the drivers in less congested routes.

Table 2.1.1 SIoT relationships in traffic domain and application.

Application	**Relationships**	**Description**
Diagnostic service	POR (Parental Object Relationship)	Vehicle communicate with friends to know if they have or had solves similar issue
Traffic information	SOR (Social Object Relationship)	Vehicles receive updated information about traffic condition from friends that usually travel in the same routes
Community services	CWOR (Co-work Object	Vehicles communicate with friends to provide information about road

	Relationship)	conditions or maintenance

Table 2.1.1 shows some typical applications of social relationships among vehicles in traffic domain. The combination of these relationships create social network in traffic domain where vehicles can gather information in a decentralized manner by navigating the network from friend to friend like humans do in social network.

Based on the above mentioned ideas, we exploited SIoT concept in traffic domain and created traffic network. In our research, we have created traffic network which actually acts like a network of Internet of Things and considered each vehicle as an object of Internet of Things (IoT). For our research purpose we have assumed that vehicles autonomously exchange their local information or social profile. The main idea is that devices with similar characteristics and profile can share best practice to solve problems already face by friends. One vehicle can know traffic information from other vehicle. If this continues, vehicle will be able to pass information to its friend vehicle about its own destination route. It will also be able to receive information from its friend vehicles about their source route. The main innovation of this paper, with respect to other IoT platforms, are the possibility of the vehicles to create their own relationships, based on the rules set by the owners and to create group of interest as it happens in human social networks. We also performed experiments on network properties such as local clustering coefficient, giant component, average path length etc. in order to analyze traffic condition. We also found percentage or each type or vehicles in traffic network while simulating traffic network in Gephi [22].

Chapter 3

Algorithm and Working Principles

This chapter describes how our data was collected and which rules and principles we considered for collecting our dataset. This chapter also describes which network properties we used and why we used those for our analysis.

3.1 Data collection

We have collected Dataset 01 for Bijoy Sarani junction from Google Maps. We have collected Dataset 02 from Bing Maps and Dataset 03 from Yahoo Maps for the same location. Now, we will discuss about analysis of these three datasets.

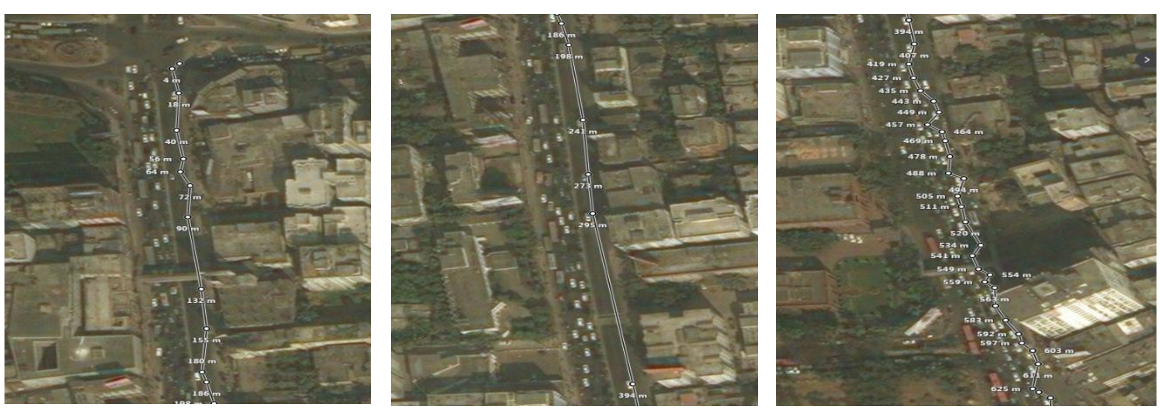


Figure 3.1.1. Satellite images from different maps

Figure 3.1.2. Distance measurements from Bing map Satellite view

Figure 3.1.3. Whole topology of Bijoy Sarani from Google map Satellite view.

We have collected a total of 20 photos on an average of each of the Google map, Bing map and yahoo map to capture the Bijoy Sarani in order to manually make datasets from map using our invented novel algorithm.

3.2 Dataset structure

We have collected information about vehicles from Google map satellite view. In our research, assumed each vehicle as a node and a node can build relationship with all nodes which are one hop away from that node. We made two different files for nodes and edges in CSV format.

In Nodes file we have following fields:

1. **Id:** We have assigned a unique id for each vehicle. Id of any two vehicles will never match.
2. **Category**: It represents the type of the vehicle. For example, if the vehicle is a private car then we put "Private Car" in this column.
3. **Label**: Label will be same as id so that we can visualize id number of nodes while simulating in Gephi [22].
1. **Route:** It detects that the vehicle is currently in which route. For instance, it will represent whether it is moving from Firmgate to Bijoy Sarani or Bijoy Sarani to Firmgate. For our research purpose, we have denoted route names in short forms. The list of route names with full forms are given below:

Table 3.2.1. Route names and directions.

Route	Direction
T_B	Tejgaon Link to Bijoy Sarani
J_B	Jahangir Gate to Bijoy Sarani

R_B	Rokeya Avenue to Bijoy Sarani
F_B	Firmgate to Bijoy Sarani
B_R	Bijoy Sarani to Rokeya Avenue
B_J	Bijoy Sarani to Jahangir Gate
B_T	Bijoy Sarani to Tejgaon Link
B_F	Bijoy Sarani to Firmgate

In Edges file we have following fields:

2. **Source**: The vehicle acting as a source in a connection.
3. **Target**: The vehicle with which the source vehicle builds connection.
4. **Type**: Represents if the connection is directed or undirected. In our research we have assumed all connections "Undirected".
5. **Weight**: The distance between two connecting vehicles. If two vehicles are in side by side parallel position then the weight is "1" according to our assumed rules. Otherwise, we consider the value of distance between two vehicles as their weight value connecting edge.
6. **Calculated by distance**: A one digit binary value which determines if the edge value is calculated by distance or if it is assumed according to our rules.
7. **Label**: Label will be same as id so that we can visualize values of connecting edges while simulating in Gephi [22].
8. **Route**: It represents the direction the vehicle.

Id	Category	Label	Route
3001	Private Car	3001	B_F
3002	Private Car	3002	B_F
3003	CNG	3003	B_F
3004	Private Car	3004	B_F
3005	Private Car	3005	B_F
3006	Private Car	3006	B_F
3007	Private Car	3007	B_F
3008	Private Car	3008	B_F
3009	Private Car	3009	B_F
3010	Private Car	3010	B_F
3011	Private Car	3011	B_F
3012	Private Car	3012	B_F
3013	Bus	3013	B_F
3014	Private Car	3014	B_F
3015	Bus	3015	B_F

Figure 3.2.1 Node entry in dataset

Source	Target	Type	Weight	culated by distar	Label	Route
3001	3002	Undirected	1	0	1	B_F
3004	3005	Undirected	1	0	1	B_F
3005	3006	Undirected	1	0	1	B_F
3008	3009	Undirected	1	0	1	B_F
3010	3011	Undirected	1	0	1	B_F
3013	3014	Undirected	1	0	1	B_F
3016	3017	Undirected	1	0	1	B_F
3020	3021	Undirected	1	0	1	B_F
3030	3031	Undirected	1	0	1	B_F
3031	3032	Undirected	1	0	1	B_F
3033	3034	Undirected	1	0	1	B_F
3039	3040	Undirected	1	0	1	F_B
3041	3042	Undirected	1	0	1	F_B
3044	3045	Undirected	1	0	1	F_B
3046	3047	Undirected	1	0	1	F_B
3047	3048	Undirected	1	0	1	F_B
3049	3051	Undirected	1	0	1	F_B
3050	3052	Undirected	1	0	1	F_B

Figure 3.2.2 Edge entry in dataset

3.3 Data colllection rules

While collecting traffic information from Google maps satellite view, we have assumed some rules as follows:

1. A vehicle will build relationship with all the vehicles that exist within one hop distance from that vehicle. The maximum range for one hop is 100 m.
2. Edge is calculated in two ways. Those are:
    i. When two vehicles exist side by side in parallel position, in that case we did not calculated distance among those and we have assumed that the connecting edge between those two vehicles is “1”.
    ii. Except case (i), in all other cases we have measured distance between two particular vehicles from Google map satellite view and considered the distance between two vehicles as the value of their connecting edge.

3.4 Algorithm

We have developed an algorithm based on our assumptions that we considered during data collection. The algorithm is illustrated in the next page.

```
Data: The traffic domain
Result: A complex network
initialization;
for all the vehicle v in the domain do
    for all the neighbor vehicles within one hop of v do
        if the hope distance is within 100 meter then
            create friendship with the neighbor vehicle;
            if the neighbor vehicle is at sideways then
                assign 1 as edge weight;
            else
                assign their distance as edge weight;
            end
        end
    end
    if the vehicle v is at the edge of a junction then
        for all the vehicle moving in the same side of road over the junction do
            for all the neighbor vehicle within one hop do
                create friendship with the neighbor vehicle;
                assign their distance as edge weight;
            end
        end
    end
end
```

Figure 3.4.1. Algorithm

3.5 Work flow

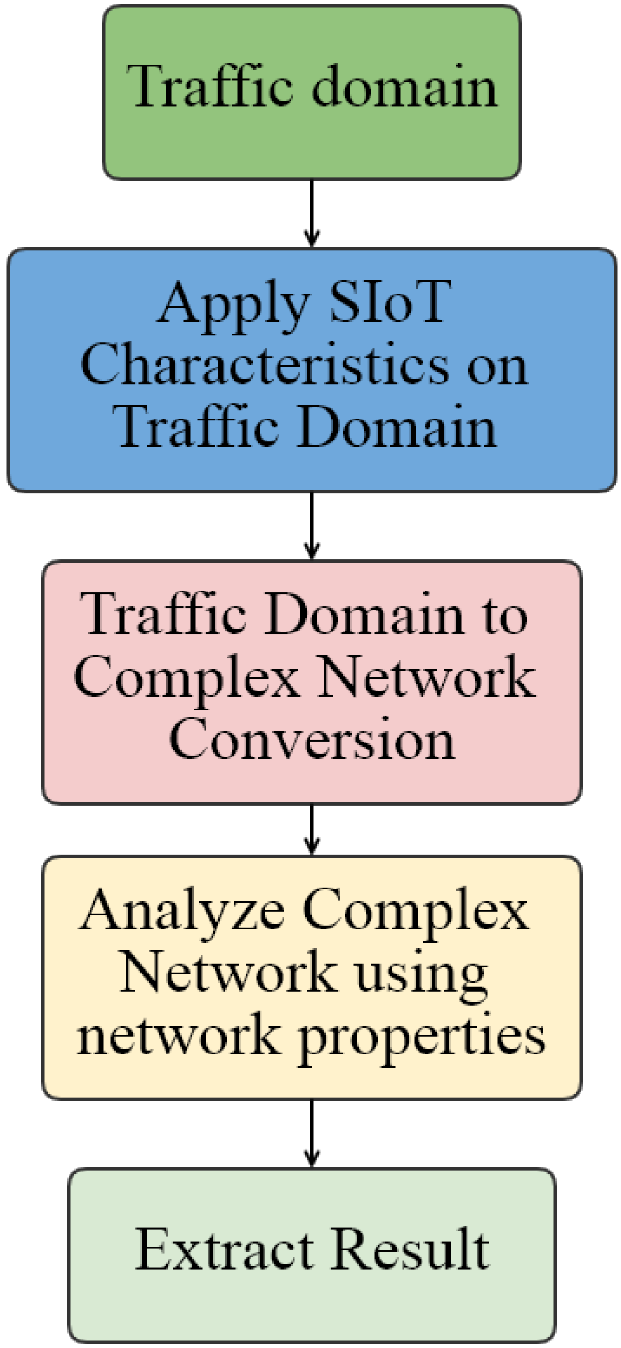


Figure 3.5.1. Work flow

In our work flow we have:

1) Collected data and created traffic domain.
2) Applied characteristics of Social Internet of Things (SIoT) on traffic domain.
3) Converted traffic domain into a complex network.
4) Analyzed complex network using network properties.
5) Extracted the result for network analysis.

Chapter 4

Simulations and Analysis

Since we found no available data for our research, we had collect data from satellite view of online maps. The data we collected for Google Maps was for year 2013 and the data we collected for Bing Maps was for year 2017.

4.1 Network analysis

This chapter describes how networks of dataset 01, dataset 02 and dataset 03 behave and what values of network properties we gain from those networks. From traffic domain we have built a complex topology of the network that has been extracted for each of the three datasets. To make the topology from dataset, we have used Forced Atlas 2.0 algorithm to represent the graph where the scaling amount was 500 and strong gravity had been imposed on the network view in order the keep the graph centered and round shape so that we can have a deep look into the topology and do necessary analysis in order to extract valuable information from the topology like amounts of a particular node, giant component, amount of a particular type of vehicle in the giant component, their combination in the whole topology, clustering coefficient etc. These information's are really important for our analysis as these information's give us valuable observations to analysis the network.

4.1.1 Total topology of the network

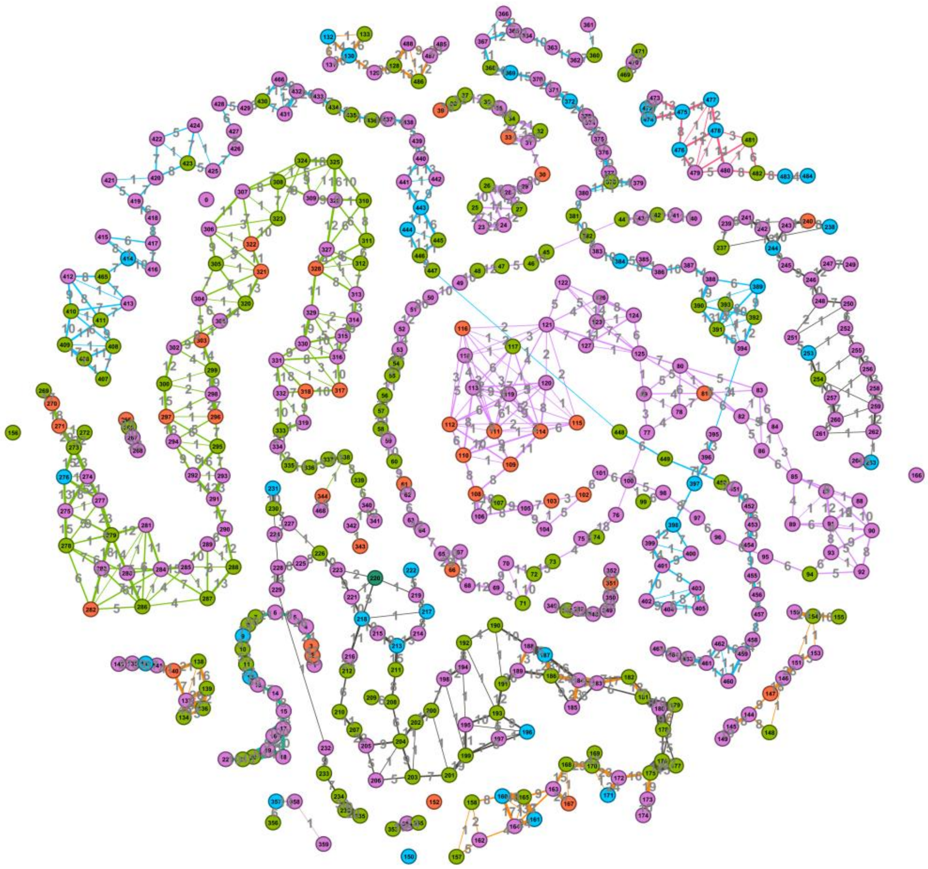


Figure 4.1.1.1. Network showing vehicle categories built from Dataset 01

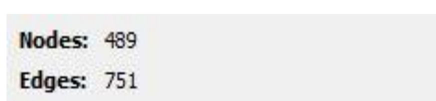


Figure 4.1.1.2. Amount of nodes and edges in network built from Dataset 01

Figure 4.1.1.3. Percentage of vehicles from different categories in the network built from Dataset 01

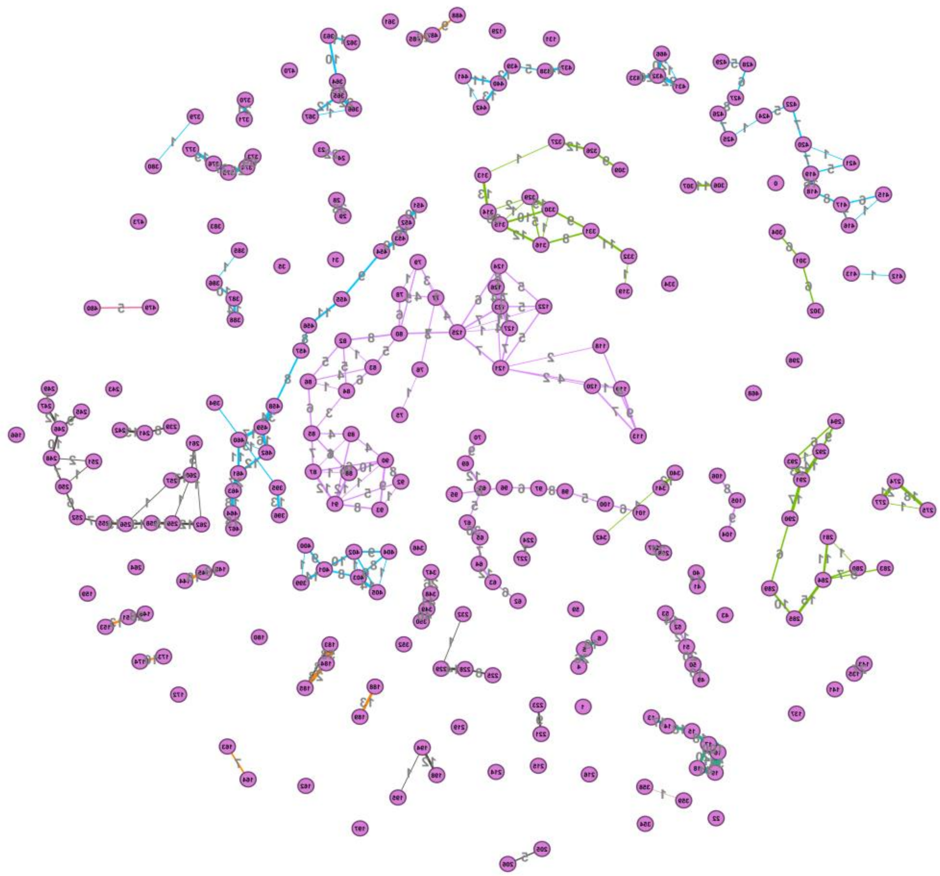


Figure 4.1.1.4. Network consisting with private car built from Dataset 01

Figure 4.1.1.5. Amount of private cars in the network built from Dataset 01

There are total 489 vehicles and 751 amount of connection in between them in the network built from dataset 01. About 54.4% of the vehicles are private car which is 266 vehicles in the network.

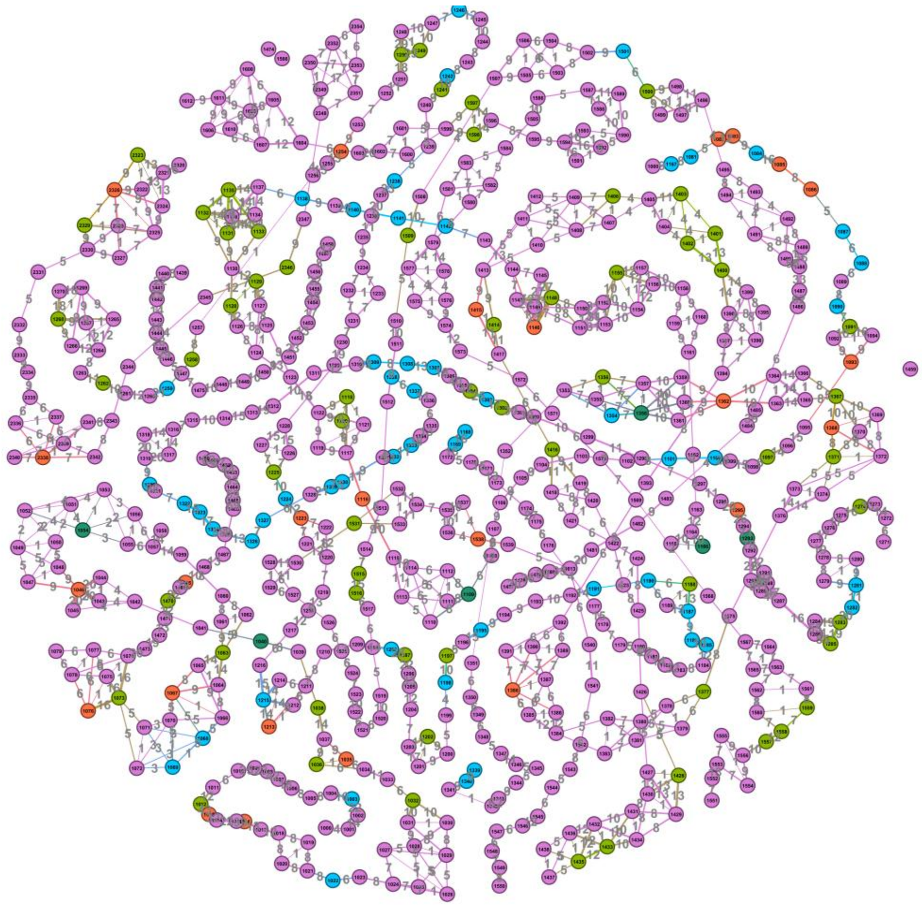


Figure 4.1.1.6. Network showing vehicle categories built from Dataset 02

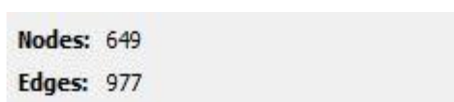


Figure 4.1.1.7. Amount of nodes and edges in network built from Dataset 02

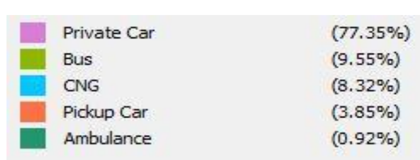


Figure 4.1.1.8. Percentage of vehicles from different categories in the network built from Dataset 02

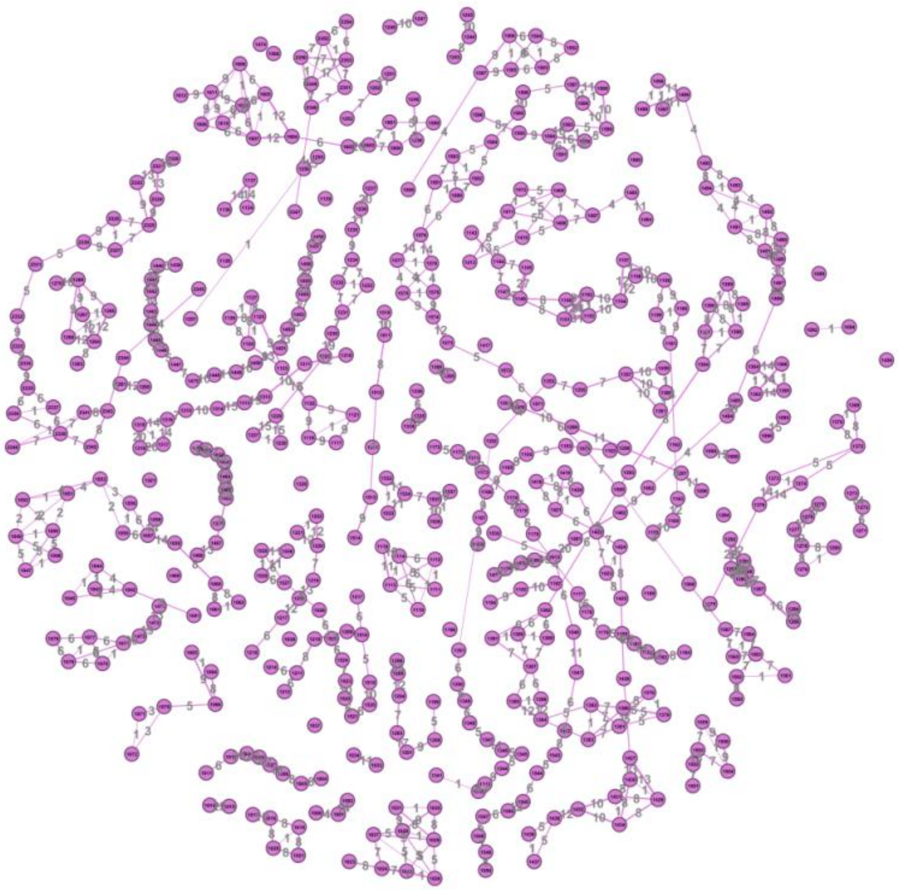


Figure 4.1.1.9. Network consisting with private car built from Dataset 02

Figure 4.1.1.10. Amount of private cars in the network built from Dataset 02

There are total 649 vehicles and 977 amount of connection in between them in the network built from dataset 02. About 77.35% of the vehicles are private car which is total 502 private cars in the network.

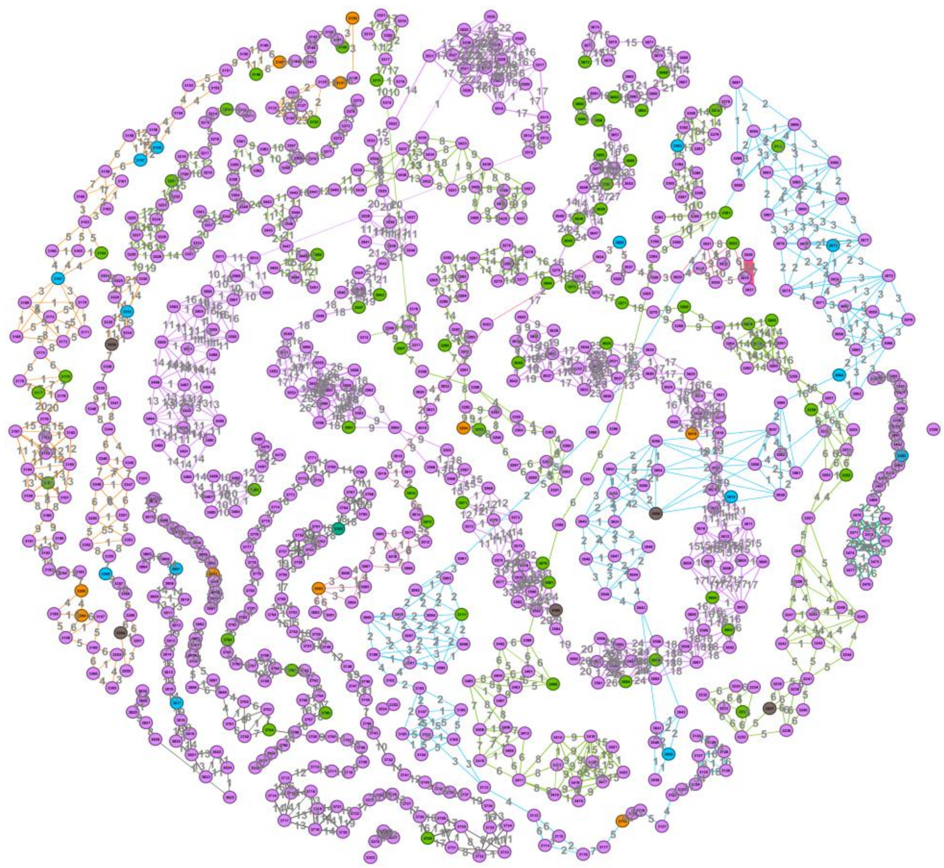


Figure 4.1.1.11. Network showing vehicle categories built from Dataset 03

Nodes: 827
Edges: 1749

Figure 4.1.1.12. Amount of nodes and edges in network built from Dataset 03

Private Car	(88.75%)
Bus	(7.62%)
Pickup Car	(1.69%)
CNG	(1.21%)
Ambulance	(0.6%)
Ambulane	(0.12%)

Figure 4.1.1.13. Percentage of vehicles from different categories in the network built from Dataset 03

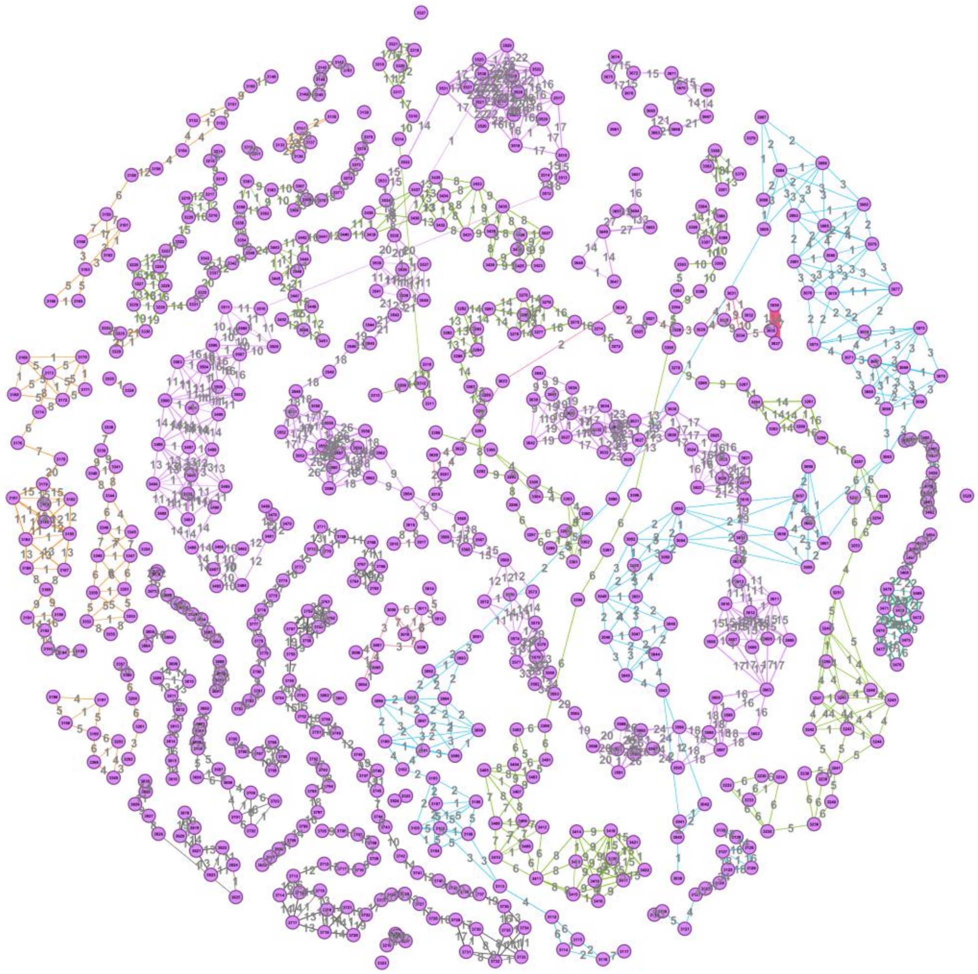


Figure 4.1.1.14. Network consisting with private car built from Dataset 03

Nodes: 734 (88.75% visible)
Edges: 1391 (79.53% visible)

Figure 4.1.1.15. Amount of private cars in the network built from Dataset 03

There are total 827 vehicles and 1749 amount of connection in between them in the network built from dataset 03. About 88.75% of the vehicles are private car which is 734 private cars in the network.

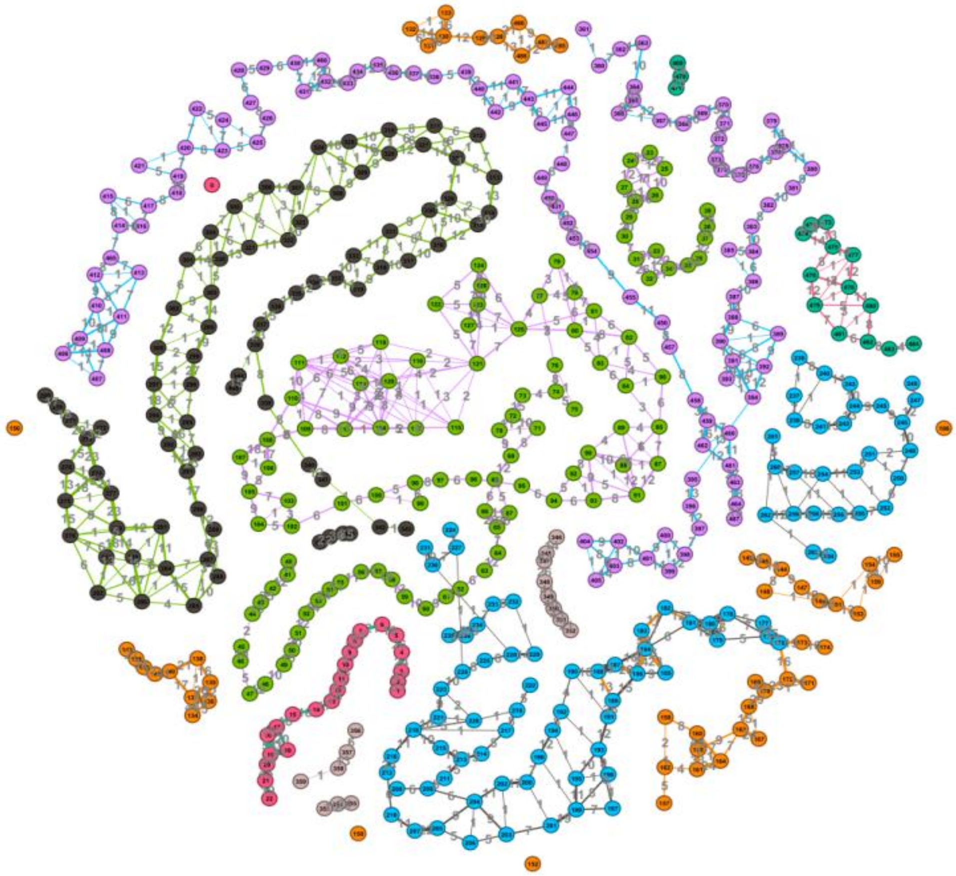


Figure 4.1.1.16. Network showing different vehicle routes built from Dataset 01

Figure 4.1.1.17. Amount of vehicles in a particular route of the network built from Dataset 01

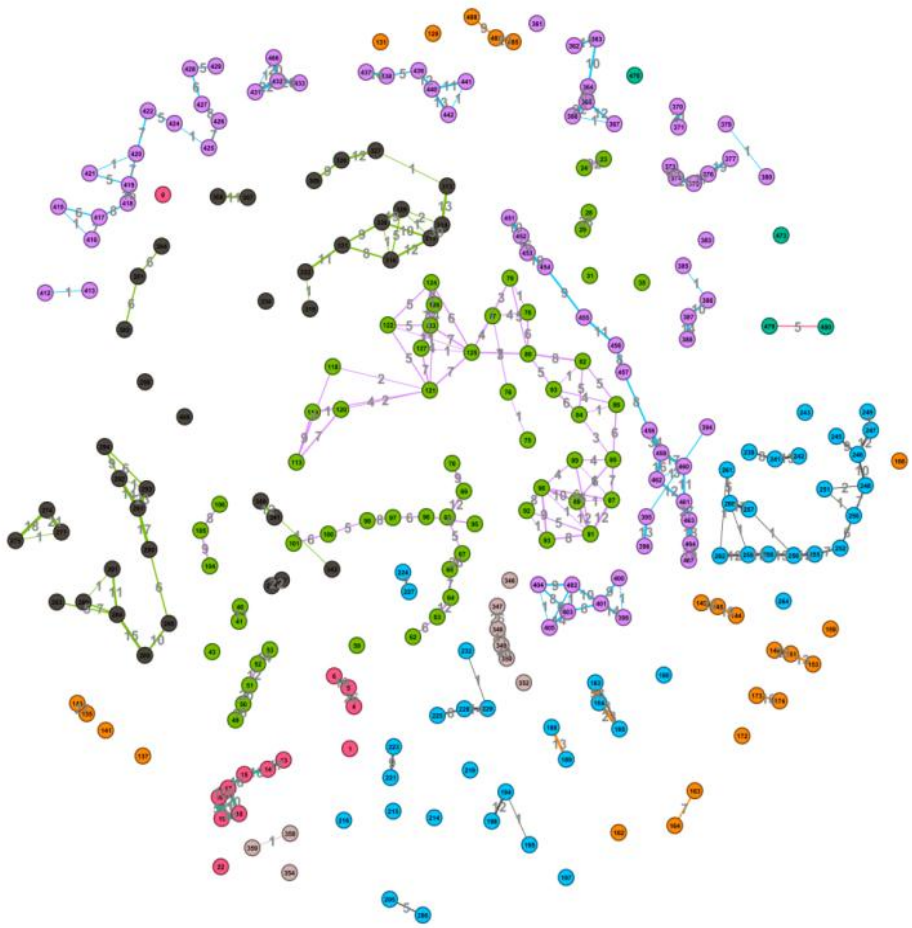


Figure 4.1.1.18. Network showing private car routes built from Dataset 01

There are at most 22.09% vehicles are passing by Tejgaon to Bijoy Sarani street. Among them majority of the vehicles are private car as we can see from the above figure. The rout Jahangirgate to Bijoy Sarani has the second highest amount of vehicle as well as private car in the network.

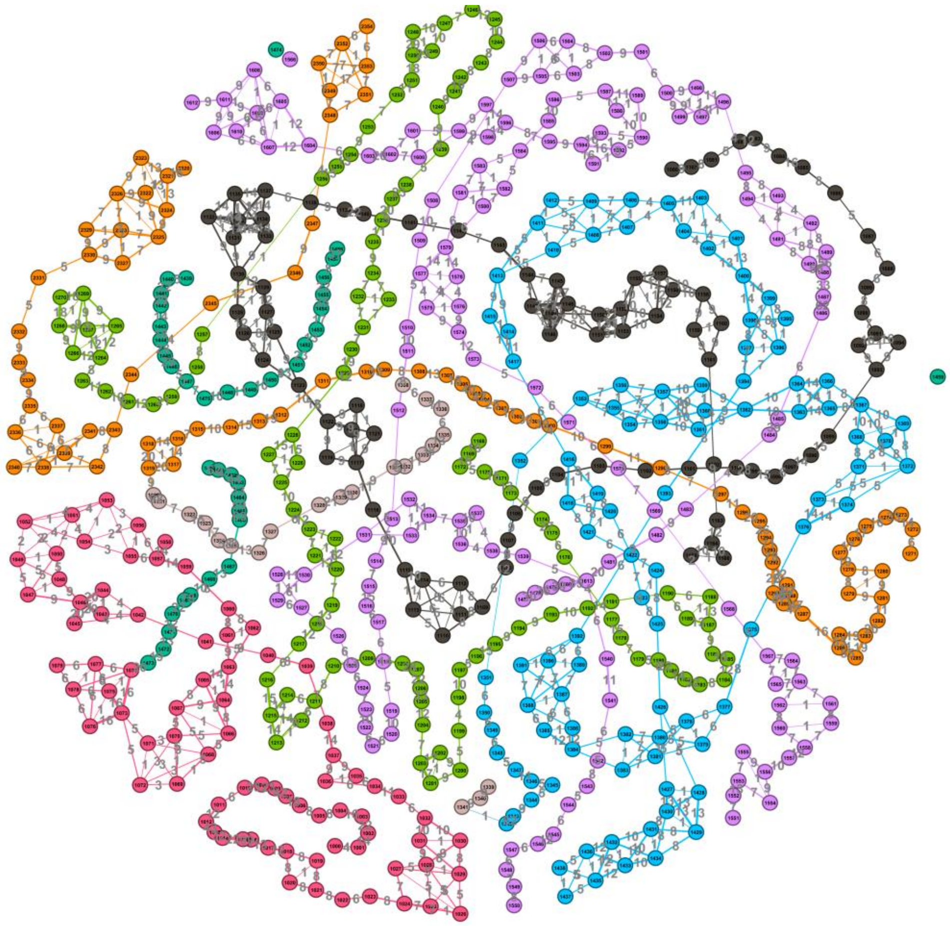


Figure 4.1.1.19. Network showing different vehicle routes built from Dataset 02

Figure 4.1.1.20. Amount of vehicles in a particular route of the network built from Dataset 02

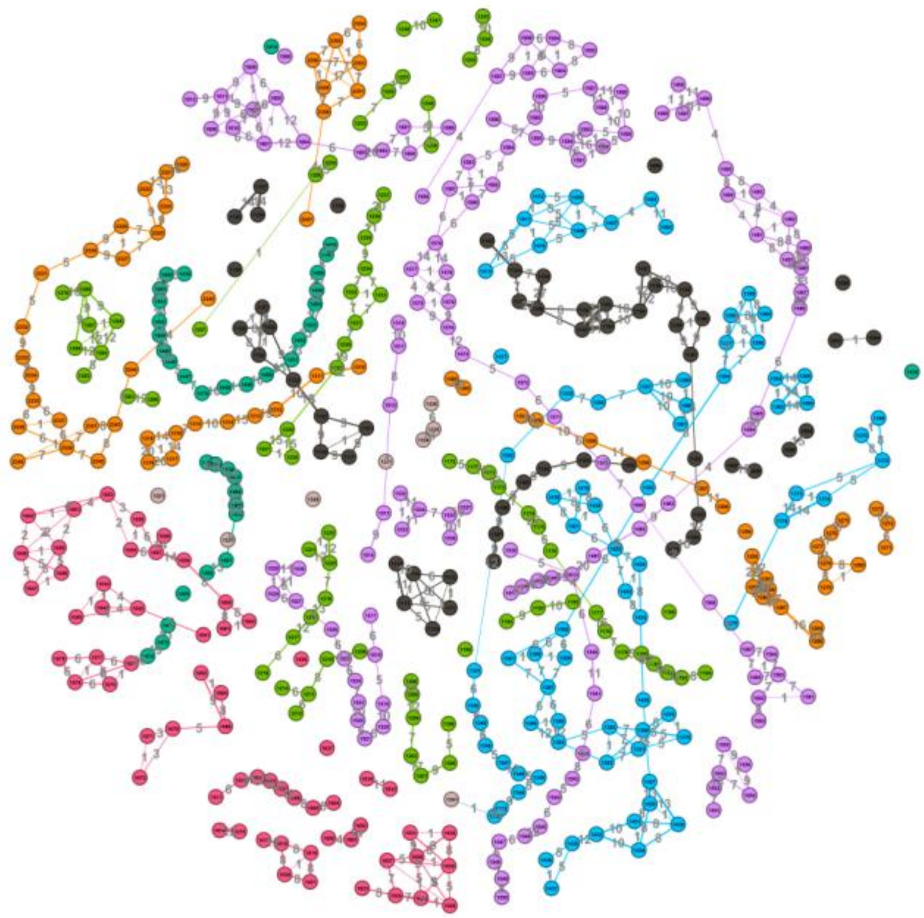


Figure 4.1.1.21. Network showing private car routes built from Dataset 02

There are at most 21.11% vehicles are passing by Tejgaon to Bijoy Sarani street. Among them majority of the vehicles are private car as we can see from the above figure. The rout Bijoy Sarani to Jahangirgate has the second highest amount of vehicle as well as private car in the network which is 15.87%.

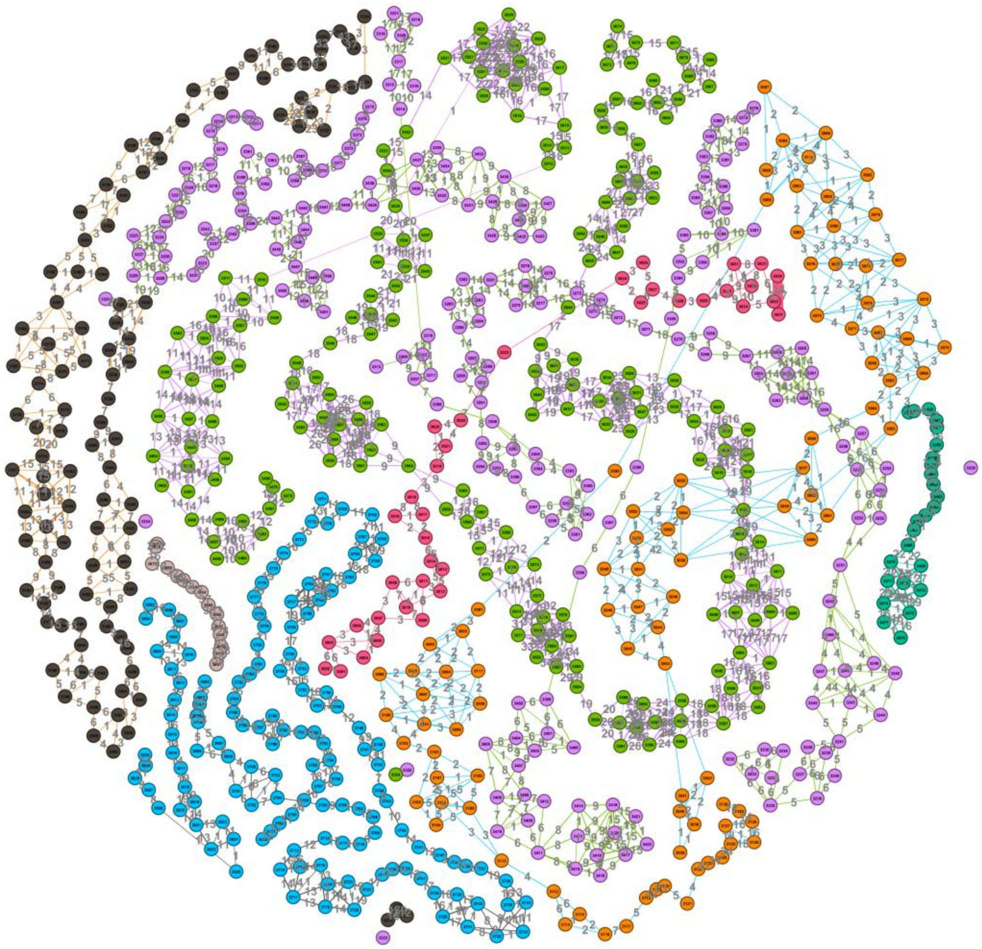


Figure 4.1.1.22. Network showing different vehicle routes built from Dataset 03

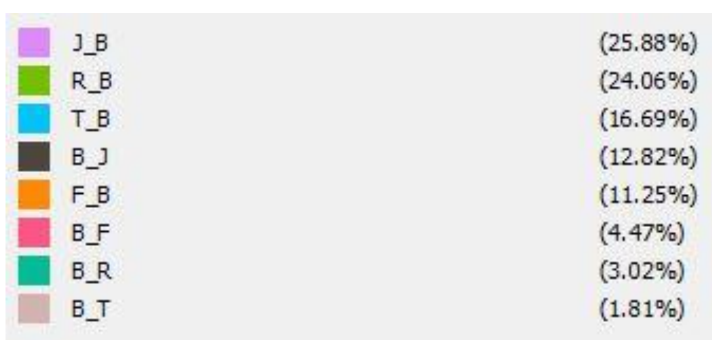


Figure 4.1.1.23. Amount of vehicles in a particular route of the network built from Dataset 03

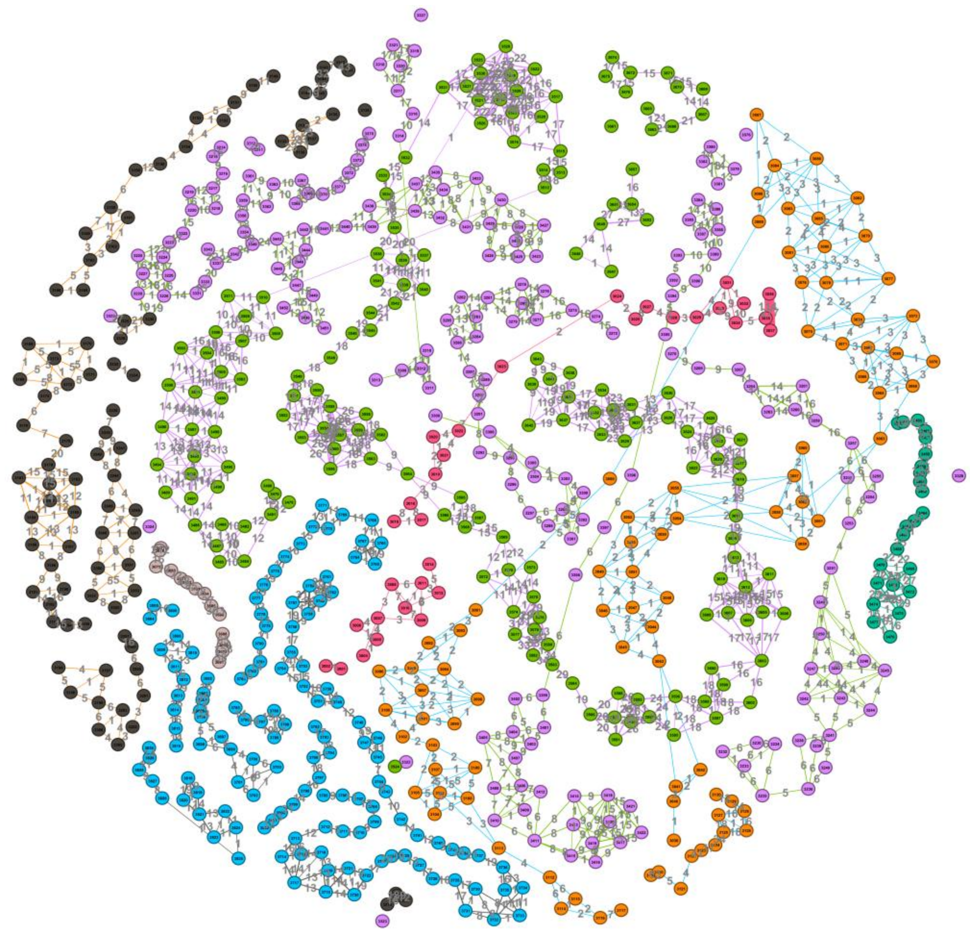


Figure 4.1.1.24. Network showing private car routes built from Dataset 03

There are at most 25.88% vehicles are passing by Jahangir gate to Bijoy Sarani street. Among them majority of the vehicles are private car as we can see from the above figure. The rout Rokeya Avenue to Bijoy Sarani has the second highest amount of vehicle as well as private car in the network which is 24.06%.

4.1.2 Clustering coefficient analysis

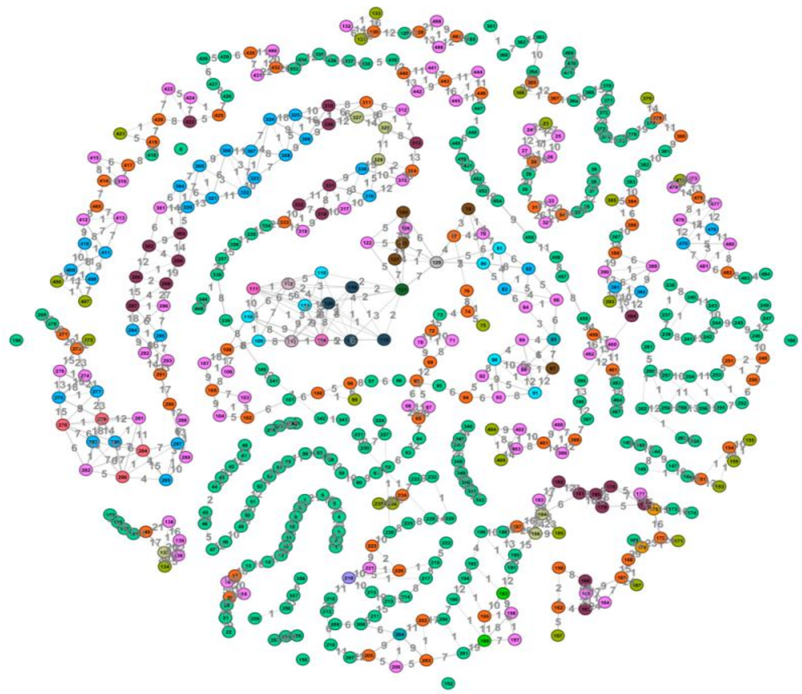


Figure 4.1.2.1. Clustering coefficients of the network built from Dataset 01

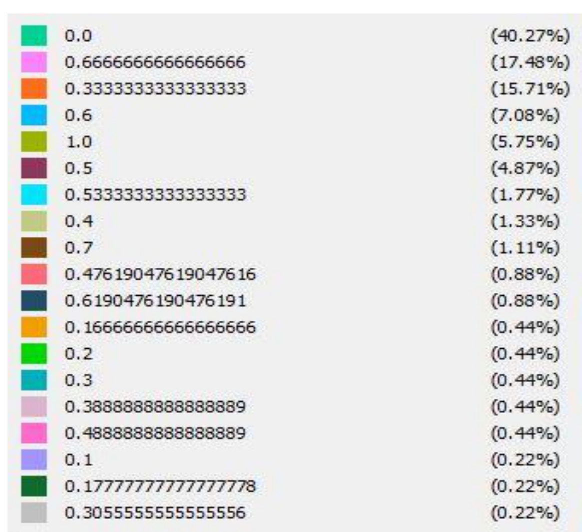


Figure 4.1.2.2. Clustering coefficient of different vehicles in the network built from Dataset 01

Figure 4.1.2.3. Network of vehicles with lowest clustering coefficient built from Dataset 01

Figure 4.1.2.4. Amount of vehicles with lowest clustering coefficient built from Dataset 01

Among all the vehicles, about 219 vehicles (44.79%) of the vehicles have the lowest clustering coefficient in the network build from dataset 01. That means these vehicles are densely connected with each other and make the street mostly crowded.

Figure 4.1.2.5. Network of private cars with lowest clustering coefficient for Dataset 01

Nodes: 123 (25.15% visible)

Edges: 67 (8.92% visible)

Figure 4.1.2.6. Amount of private cars with lowest clustering coefficient for Dataset 01

Among all the vehicles within the network a total of 123 (25.15% of the total vehicles) private cars have lowest clustering coefficient in the network built from dataset 01.

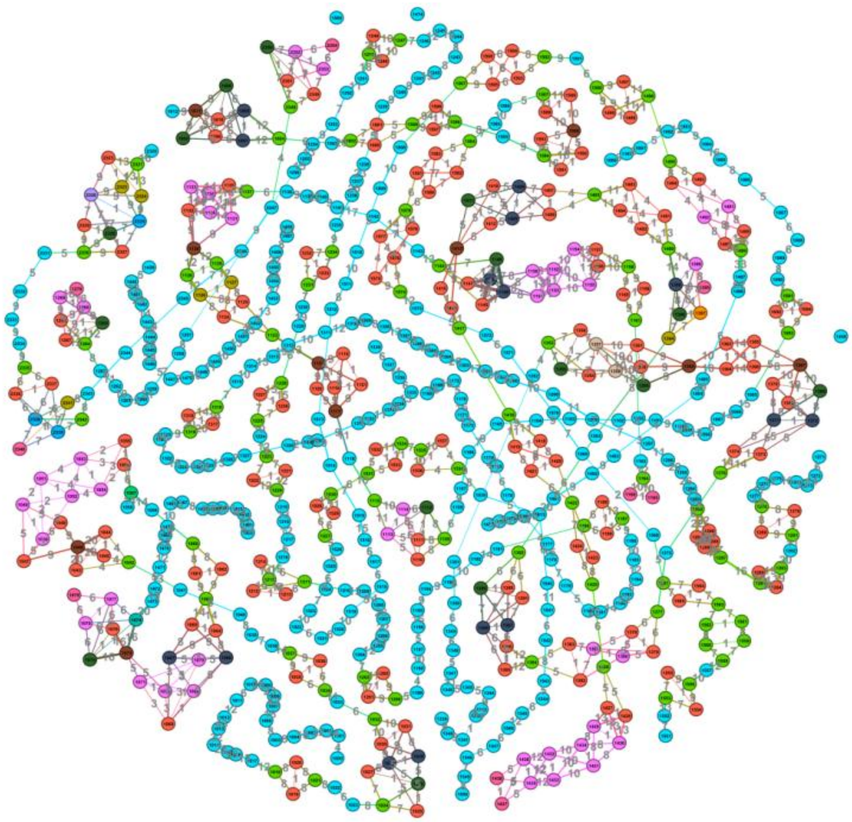


Figure 4.1.2.7. Clustering coefficients of vehicles of the network built from Dataset 02

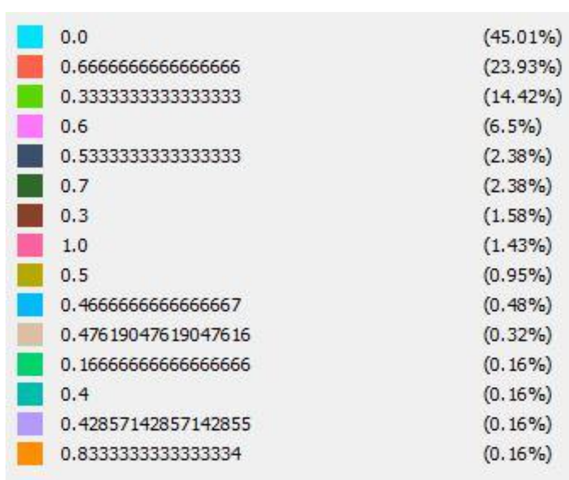


Figure 4.1.2.8. Clustering coefficient of different vehicles in the network built from Dataset 02

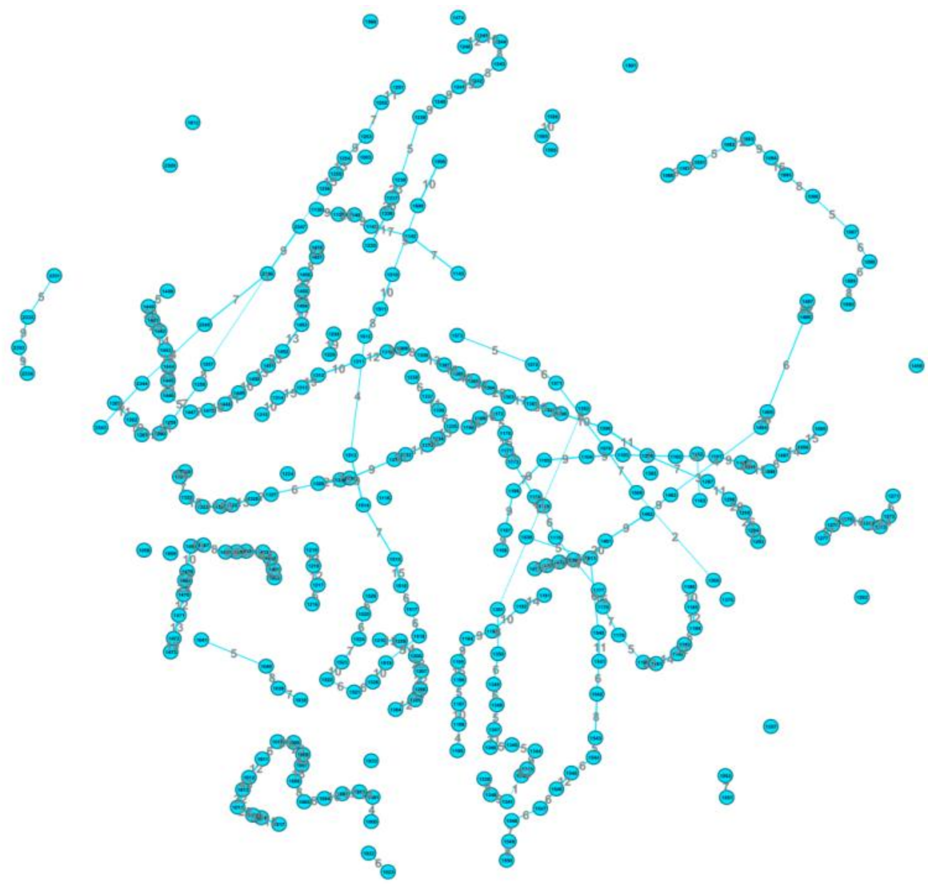


Figure 4.1.2.9. Network of vehicles with lowest clustering coefficient for Dataset 02

Figure 4.1.2.10. Amount of vehicles with lowest clustering coefficient for Dataset 02

Among all the vehicles, about 302 vehicles (46.53%) of the vehicles have the lowest clustering coefficient in the network build from dataset 02. That means these vehicles are densely connected with each other and make the street mostly crowded.

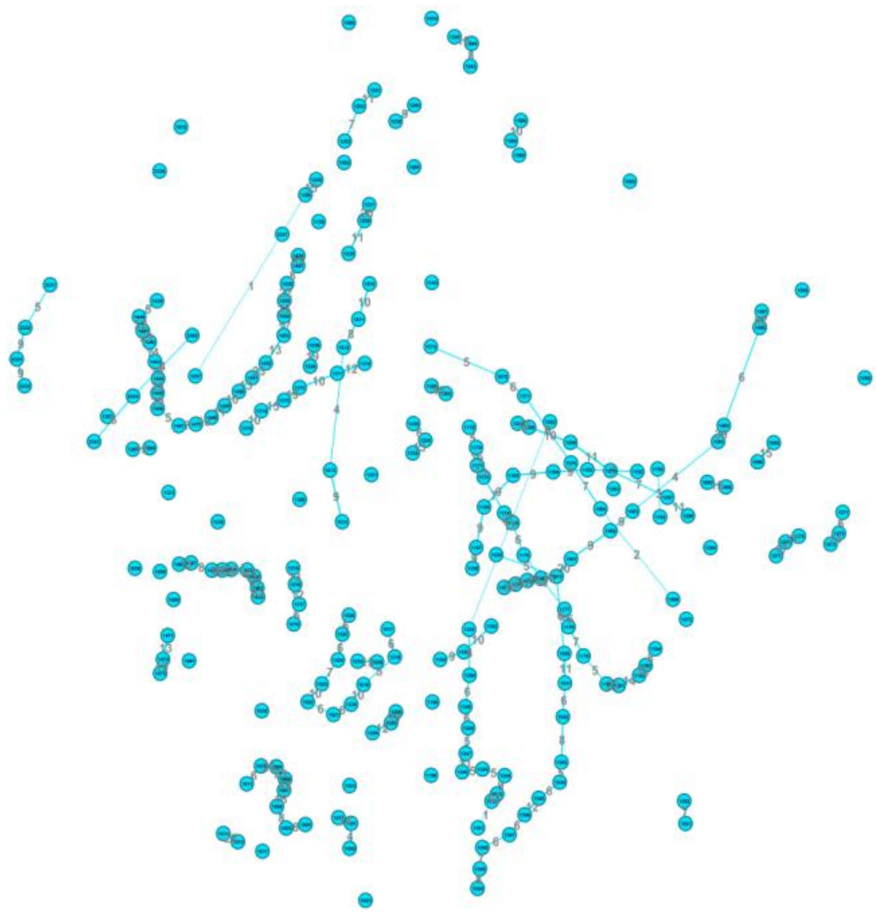


Figure 4.1.2.11. Network of private cars with lowest clustering coefficient built from Dataset 02

Nodes: 226 (34.82% visible)
Edges: 158 (16.17% visible)

Figure 4.1.2.12. Amount of private cars with lowest clustering coefficient in the network built from Dataset 02

Among all the vehicles within the network a total of 226 (34.82% of the total vehicles) private cars have lowest clustering coefficient in the network built from dataset 02.

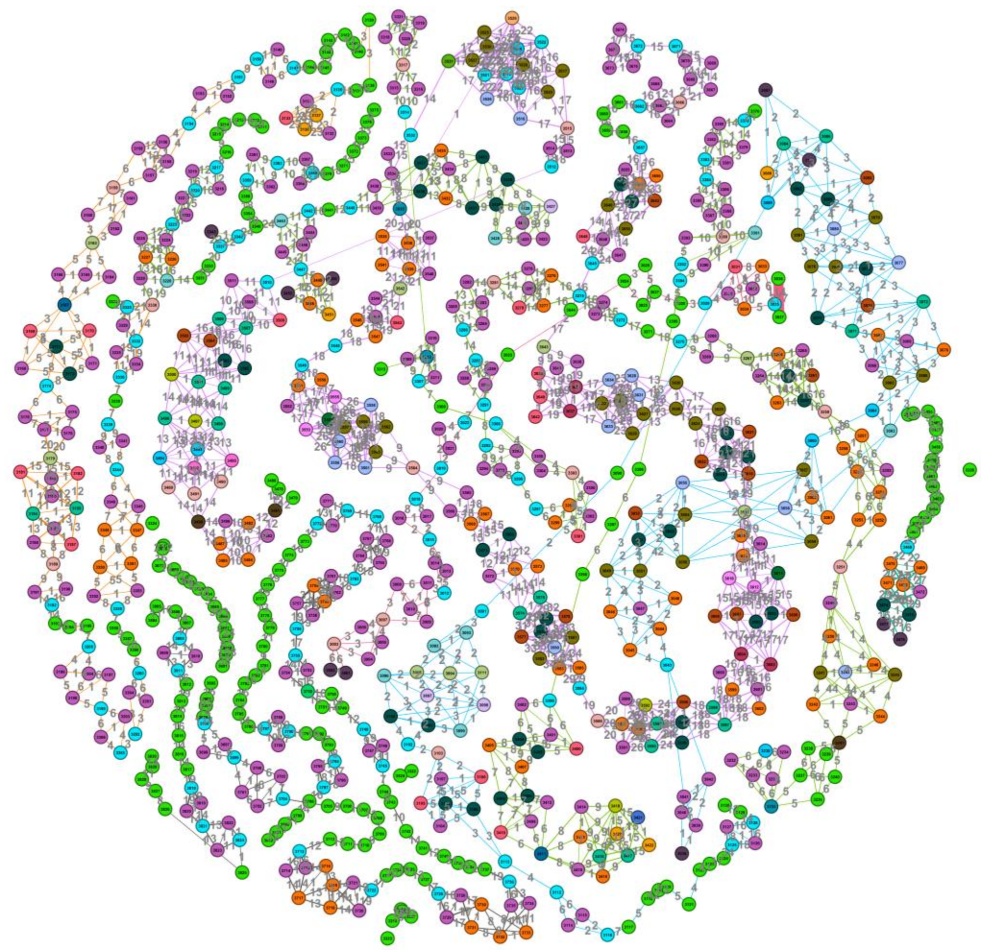


Figure 4.1.2.13. Clustering coefficients of vehicles of the network built from Dataset 03

0.6666666666666666	(27.81%)
0.0	(19.45%)
0.3333333333333333	(12.59%)
0.6	(9.98%)
0.5333333333333333	(5.24%)
0.47619047619047616	(4.49%)
0.42857142857142855	(2.49%)
0.3	(2.37%)
0.7	(2.37%)
0.5714285714285714	(2%)
0.6190476190476191	(2%)
0.4	(1.25%)
1.0	(1.25%)
0.26666666666666666	(1.12%)
0.5	(0.87%)
0.8333333333333334	(0.75%)
0.35555555555555557	(0.5%)
0.3888888888888889	(0.5%)
0.5277777777777778	(0.5%)
0.13333333333333333	(0.37%)
0.2	(0.37%)
0.5238095238095238	(0.37%)
0.23809523809523808	(0.25%)
0.38095238095238093	(0.25%)
0.4888888888888889	(0.25%)
0.16666666666666666	(0.12%)
0.19047619047619047	(0.12%)
0.43636363636363634	(0.12%)
0.4444444444444444	(0.12%)
0.8	(0.12%)

Figure 4.1.2.14 Clustering coefficient of different vehicles in the network built from Dataset 03

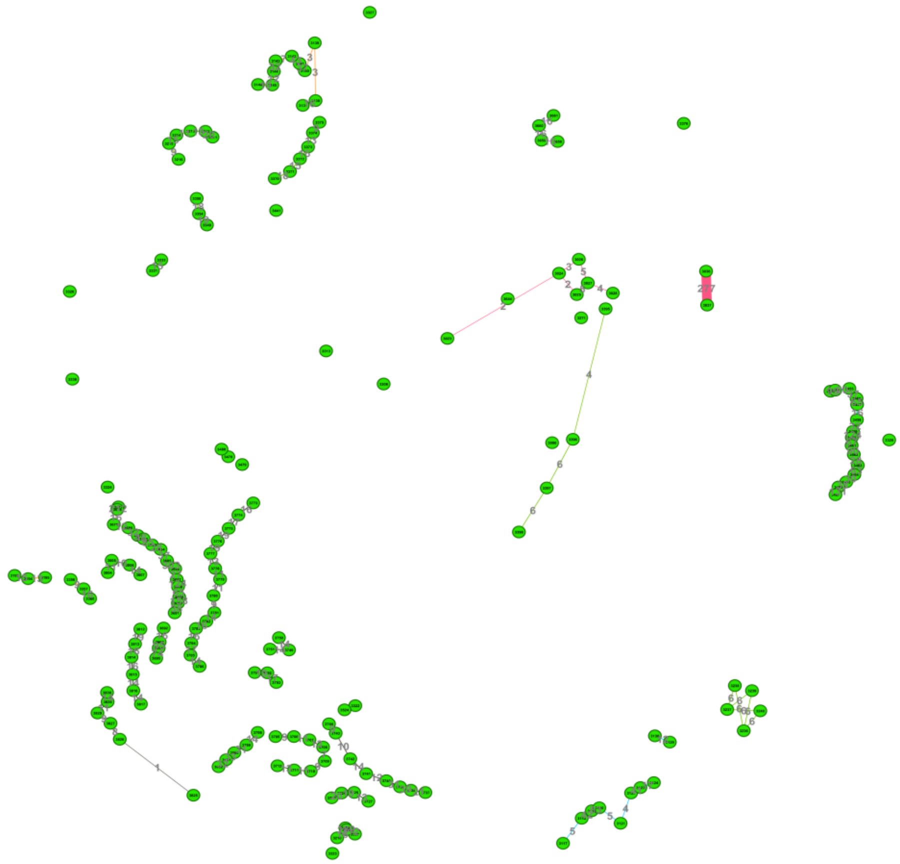
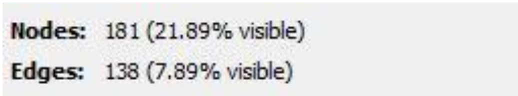


Figure 4.1.2.15. Network of vehicles with lowest clustering coefficient built from Dataset 03



Nodes: 181 (21.89% visible)
Edges: 138 (7.89% visible)

Figure 4.1.2.16. Amount of vehicles with lowest clustering coefficient for Dataset 03

Among all the vehicles, about 181 vehicles (21.89%) of the vehicles have the lowest clustering coefficient in the network build from dataset 03. That means these vehicles are densely connected with each other and make the street mostly crowded.

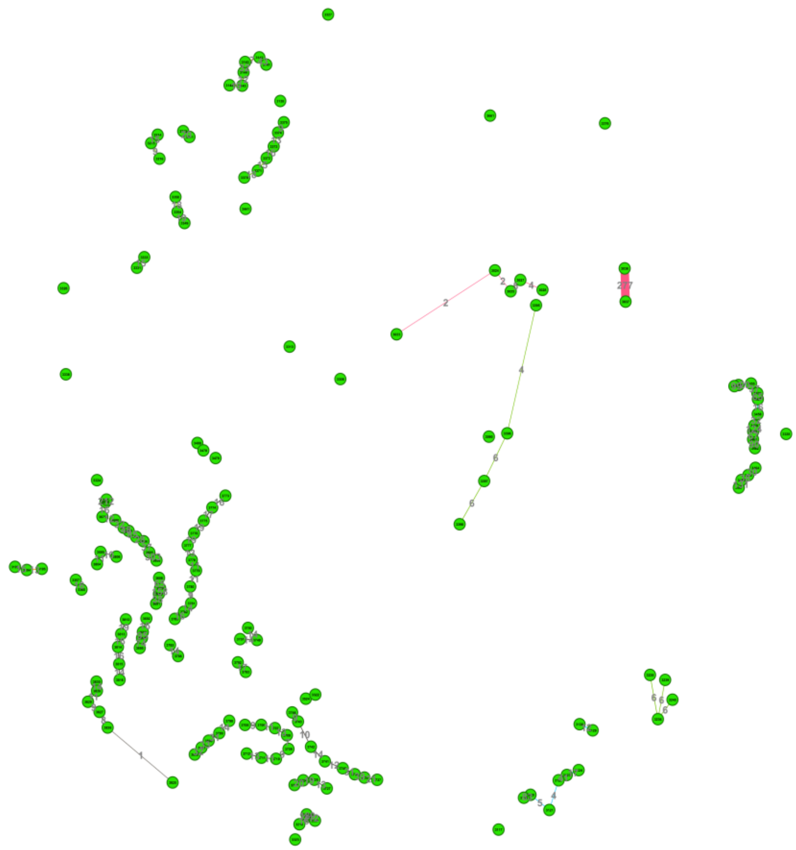


Figure 4.1.2.17. Network of private cars with lowest clustering coefficient built from Dataset 03

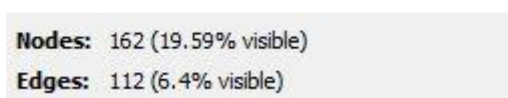


Figure 4.1.2.18. Amount of private cars with lowest clustering coefficient in the network built from Dataset 03

Among all the vehicles within the network a total of 162 (19.59% of the total vehicles) private cars have lowest clustering coefficient in the network built from dataset 03.

4.1.3 Giant component

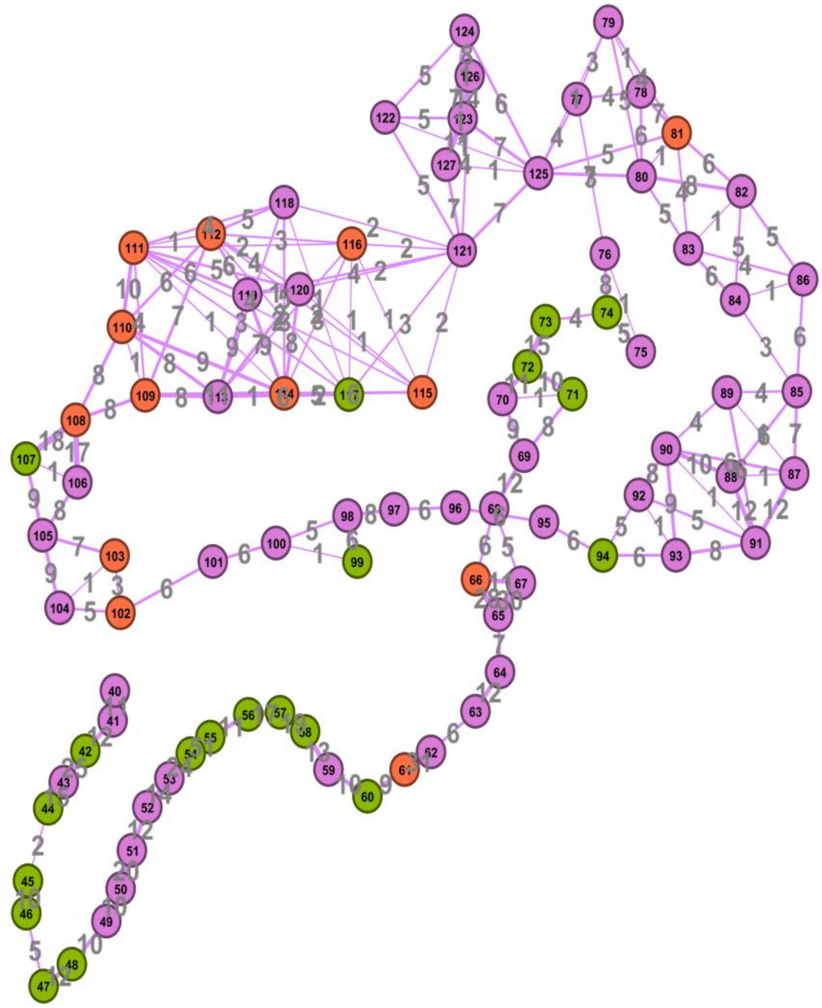


Figure 4.1.3.1. Vehicle of different category in the giant component of the network built from Dataset 01

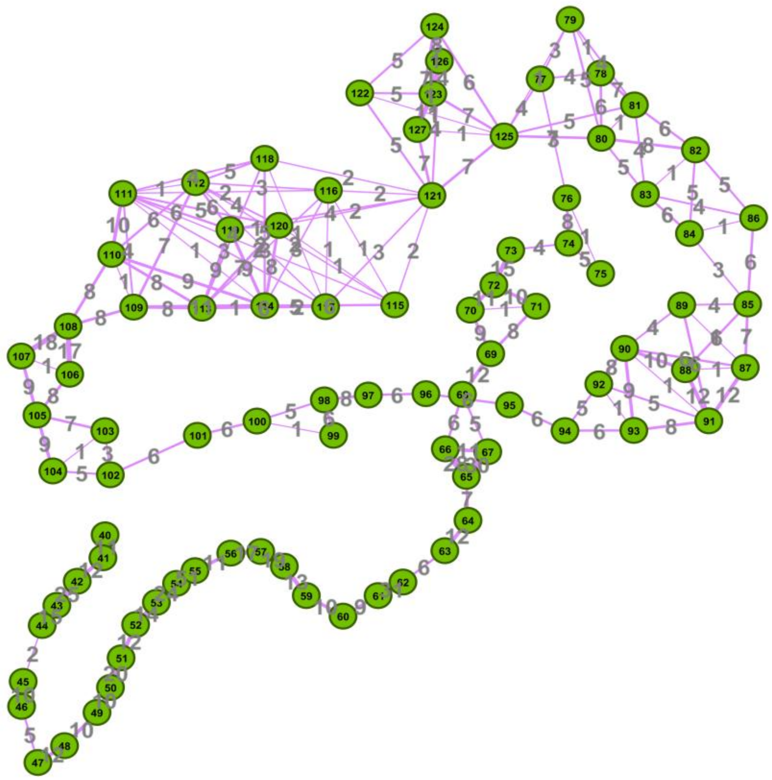


Figure 4.1.3.2. Showing route in Giant component of the network built from Dataset 01 (J_B)

Figure 4.1.3.3. Amount of nodes and edges in giant component for Dataset 01

Among all the vehicles, about 88 vehicles (18% of the total vehicles) are responsible for the giant component in the network built from dataset 01. That means these vehicles are responsible for the most huge congestion and blockage in the route Jahangir gate to Bijoy Sarani.

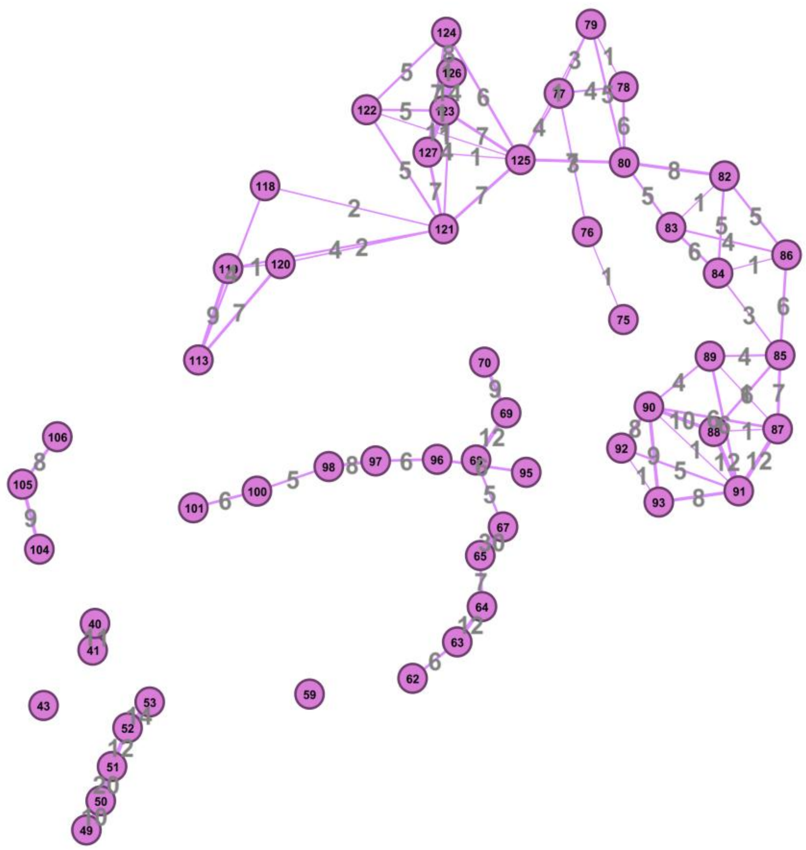


Figure 4.1.3.4. Giant component amount of private cars for Dataset 01

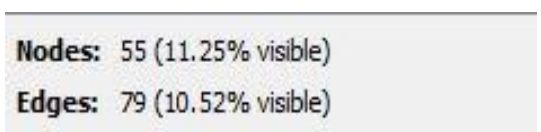


Figure 4.1.3.5. Amount of private cars in giant component for Dataset 01

Among all the vehicles, about 55 private cars (11.25% of the total vehicles) are responsible for the giant component in the network built from dataset 01. That means these private cars are responsible for the most huge congestion and blockage in the route Jahangir gate to Bijoy Sarani.

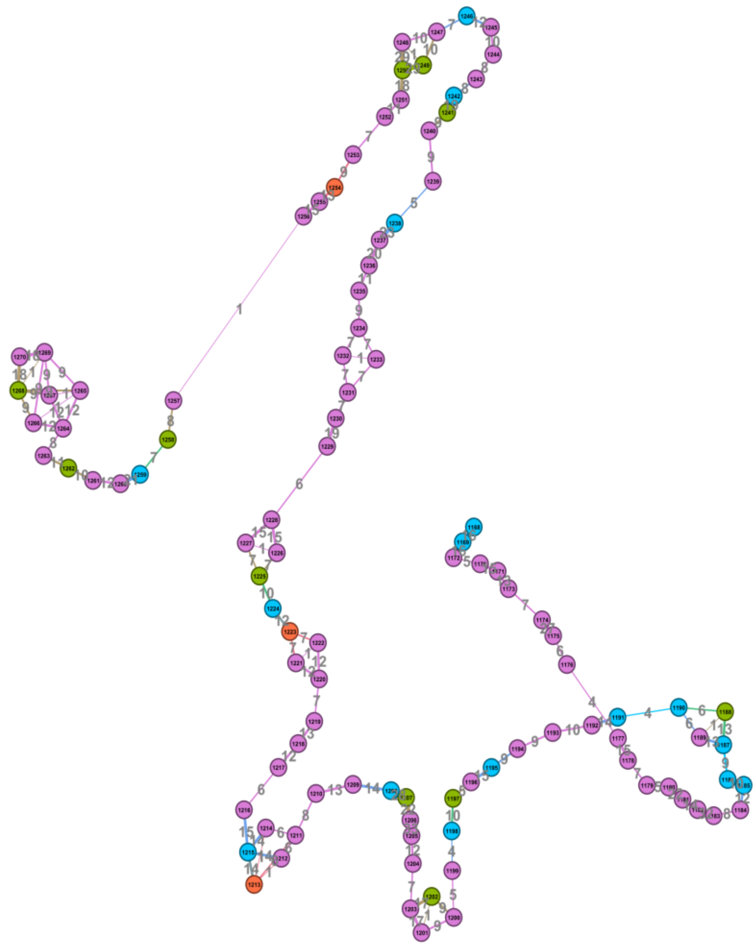


Figure 4.1.3.6. Vehicle of different category in the giant component of the network built from Dataset 02

Figure 4.1.3.7. Showing route in Giant component of the network built from Dataset 02 (B_J)

Figure 4.1.3.8. Amount of nodes and edges in giant component for Dataset 02

Among all the vehicles, about 103 vehicles (15.87% of the total vehicles) are responsible for the giant component in the network built from dataset 02. That means these vehicles are responsible for the most huge congestion and blockage in the route Bijoy Sarani to Jahangir gate.

Figure 4.1.3.9. Giant component amount of private cars for Dataset 02

Nodes: 73 (11.25% visible)
Edges: 66 (6.76% visible)

Figure 4.1.3.10. Amount of private cars in giant component for Dataset 02

Among all the vehicles, about 73 private cars (11.25% of the total vehicles) are responsible for the giant component in the network built from dataset 02. That means these private cars are responsible for the most huge congestion and blockage in the route Bijoy Sarani to Jahangir gate.

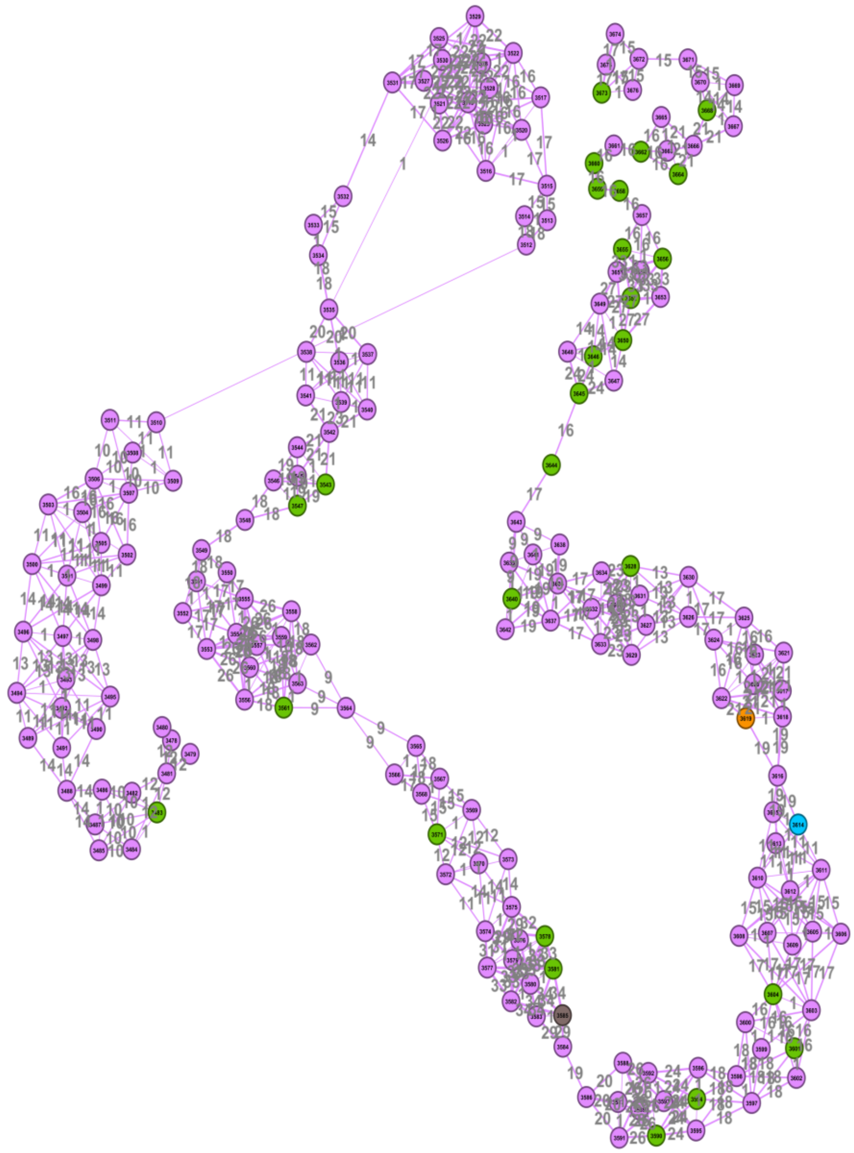


Figure 4.1.3.11. Vehicle of different category in the giant component of the network built from Dataset 03

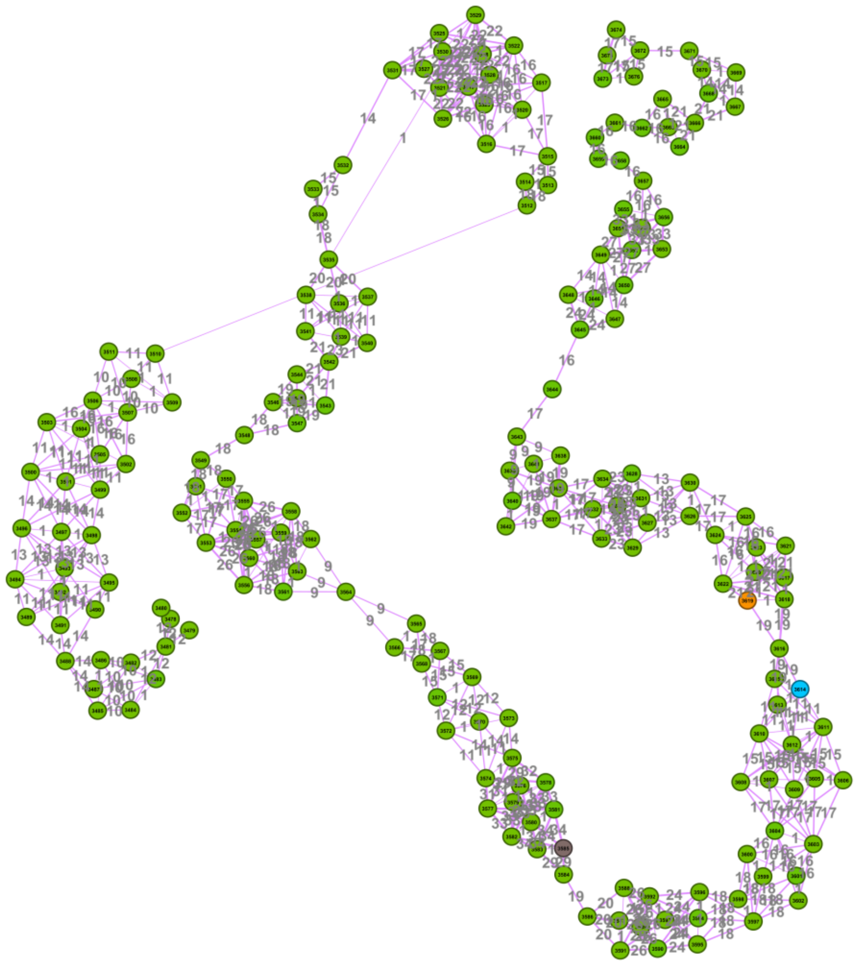


Figure 4.1.3.12. Showing route in Giant component of the network built from Dataset 03 (R_B)

Figure 4.1.3.13. Amount of nodes and edges in giant component for Dataset 03

Among all the vehicles, about 198 vehicles (23.94% of the total vehicles) are responsible for the giant component in the network built from dataset 03. That means these vehicles are responsible for the most huge congestion and blockage in the route Rokeya Avenue to Bijoy Sarani.

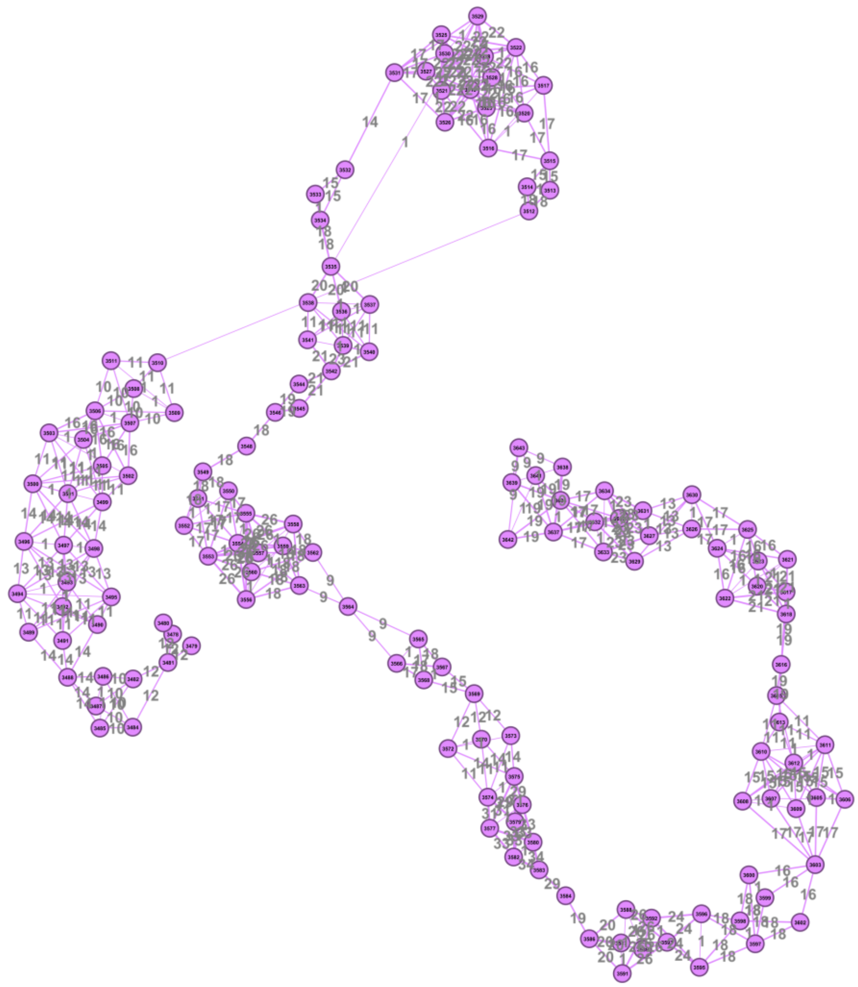


Figure 4.1.3.14. Giant component amount of private cars for Dataset 03

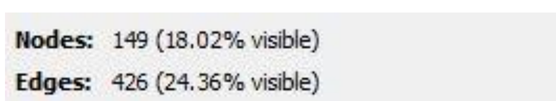


Figure 4.1.3.15. Amount of private cars in giant component for Dataset 03

Among all the vehicles, about 149 private cars (18.02% of the total vehicles) are responsible for the giant component in the network built from dataset 03. That means these private cars are responsible for the most huge congestion and blockage in the route Rokeya Avenue to Bijoy Sarani.

Table 4.1.1. Statistics of nodes and edges for different datasets.

Different filtering on network	**Dataset 01**	**Dataset 02**	**Dataset 03**
Amount of nodes and edges in the graph	**Nodes:** 489 **Edges:** 751	**Nodes:** 649 **Edges:** 977	**Nodes:** 827 **Edges:** 1749
Amount of cars in the graph	**Nodes:** 266 (54.4%) **Edges:** 245 (32.62%)	**Nodes:** 502(77.35%) **Edges:** 612 (62.64%)	**Nodes:** 734(88.75%) **Edges:** 1391 (79.53%)
Amount of nodes in giant component	**Nodes:** 88 (18%) **Edges:** 169 (22.5%)	**Nodes:** 103(15.87%) **Edges:** 126 (12.9%)	**Nodes:** 198(23.94%) **Edges:** 593 (33.91%)
Amount of nodes with lowest clustering coefficient	**Nodes:** 219 (44.9%) **Edges:** 186 (24.77%)	**Nodes:** 302(46.53%) **Edges:** 258 (26.41%)	**Nodes:** 181(21.89%) **Edges:** 138 (7.89%)
Amount of private cars in giant component	**Nodes:** 55 (11.25%) **Edges:** 79 (10.52%)	**Nodes:** 73(11.25%) **Edges:** 66 (6.76%)	**Nodes:** 149(18.02%) **Edges:** 426 (24.36%)
Amount of private cars with lowest clustering coefficient	**Nodes:** 123 (25.15%) **Edges:** 67 (8.92%)	**Nodes:** 226(34.82%) **Edges:** 158(16.17%)	**Nodes:** 162(19.59%) **Edges:** 112 (6.4%)

4.2 Graph from network properties

We have further analysed some important network properties on networks formed from dataset 01,02 and 03 to extract some graph to further discuss on the certain characterisitics in SIoT traffic doamin in order to have a deeper look into it. We have extracted graph for some key properties like clusetering coefficient distribution, degree distribution, weigted degree distributions, community size distributions, ecentrcity distributions etc. We have found some important properties in numerical values for every dataset so that we can compare them to differenciate datasets in their certain level. Finally we have put all the finding in a table.

4.2.1 Clustering coefficient distribution

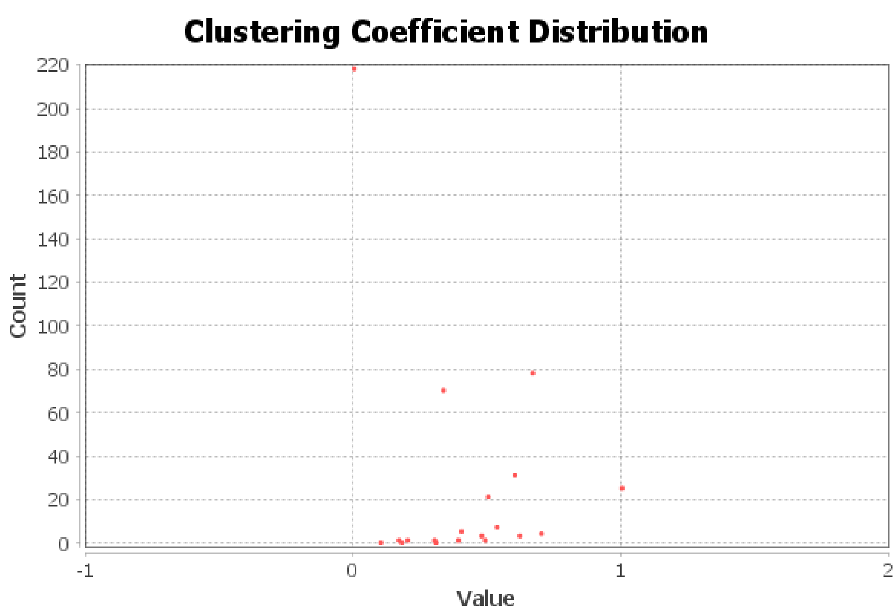


Figure 4.2.1.1. Clustering coefficient of Dataset 01

In graph theory, a clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together. The local clustering coefficient of a vertex in a graph quantifies how close its neighbors are to being a complete graph. If we look at figure 4.2.1.1 we can see that for dataset 01 the clustering coefficient is about .334. The value of all the clusters have been normalized in between 0 and 1.

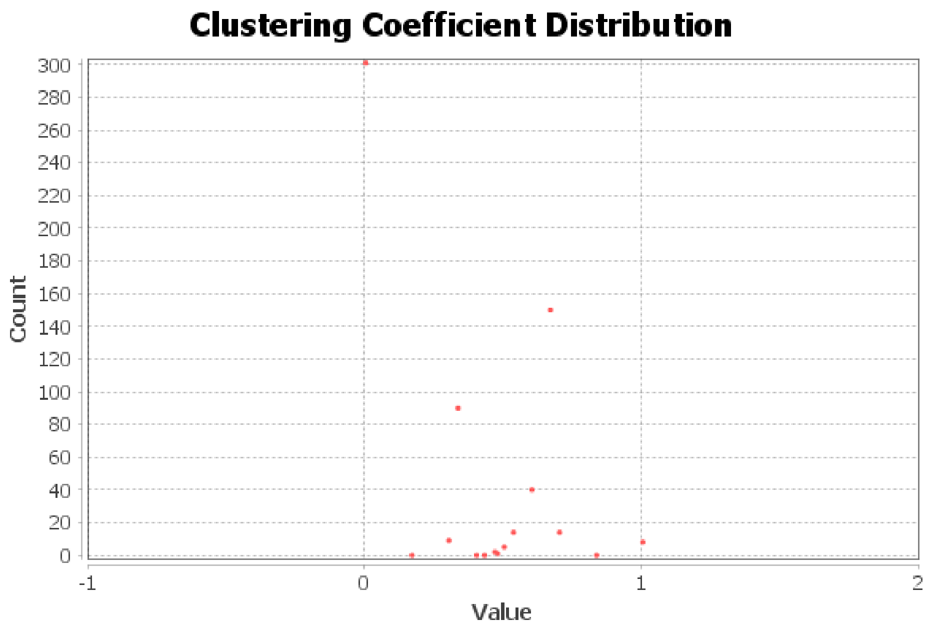


Figure 4.2.1.2. Clustering coefficient of Dataset 02

For dataset 02 as we can see from the figure 4.2.1.2 that the clusters are being normalized and the clustering coefficient of dataset 02 is .306 which is quiet smaller in comparison to the dataset 01 where the clustering coefficient was .334.

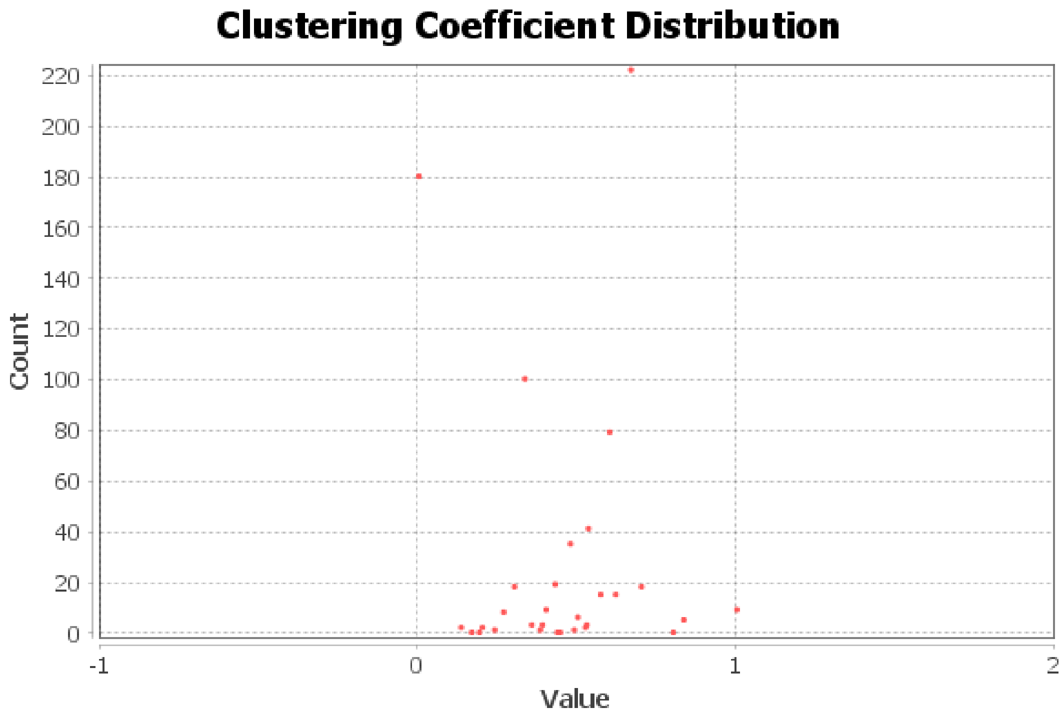


Figure 4.2.1.3. Clustering coefficient of Dataset 03

From figure 4.2.1.3 we can see the clustering coefficient of dataset 03 where most of the clusters are counted within 0 to 20 range and few of the clusters have been counted over 40. Among them only three clusters could go up to 80 plus count whereas only one cluster in the network has reach up to 220 count. The clustering coefficient has come .441 which is certainly greater than the clustering coefficients for networks built from dataset 01 and dataset 02 which were .331 and .306. Although the clustering coefficients have been standardized that means all the clustering coefficients are counted in between 0 and 1 but still there are a high distinction among the outcome from different datasets. As the dataset 03 has more vehicle and edge in it, the probability of getting some of its cluster in high count has become true.

4.2.2 Degree distribution

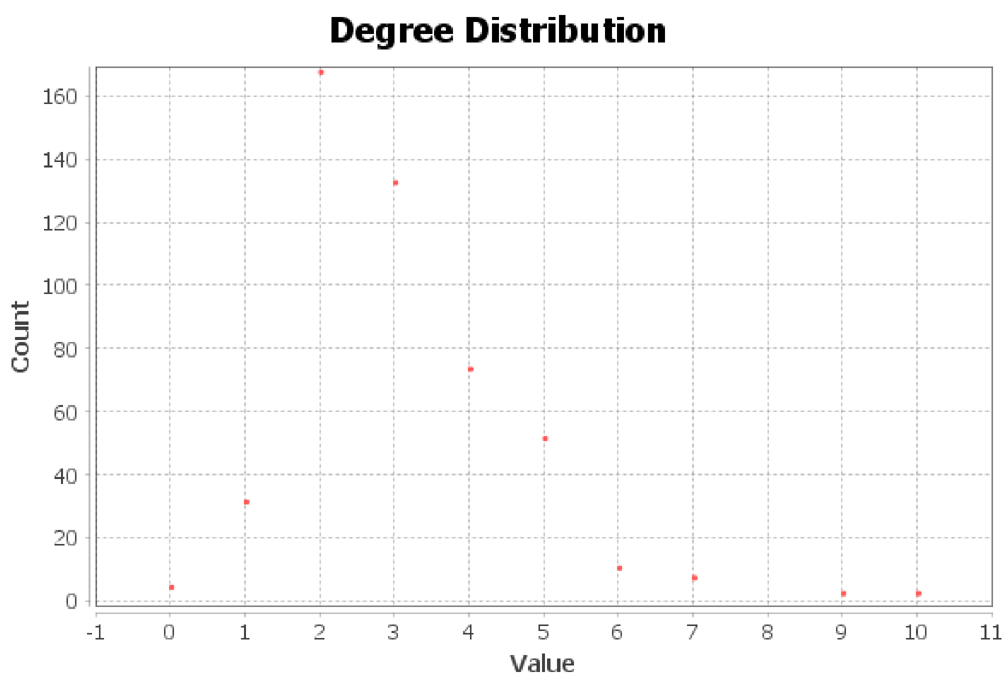


Figure 4.2.2.1. Degree distribution of Dataset 01

Figure 4.2.2.1 shows the degree distribution of nodes and edges from dataset 01. As we can see, the graph has an average degree of 3.072. Figure 4.2.2.2 shows the degree distribution of nodes and edged from dataset 02 and that graph has an average of degree 3.011 which is similar to dataset 01 as most of their degrees are normally distributed.

But in case of dataset 03 as we can see from figure 4.2.2.3 that the degree distribution is a little different what we have found for dataset 01 and dataset 02. The degree distribution for dataset 03 is 4.230.

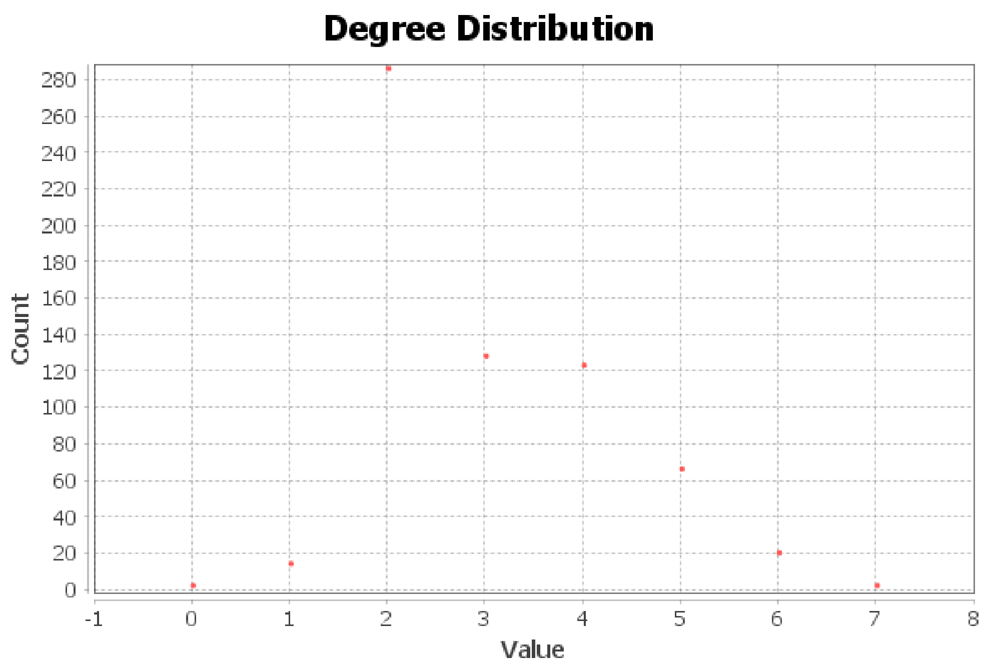


Figure 4.2.2.2. Degree distribution of Dataset 02

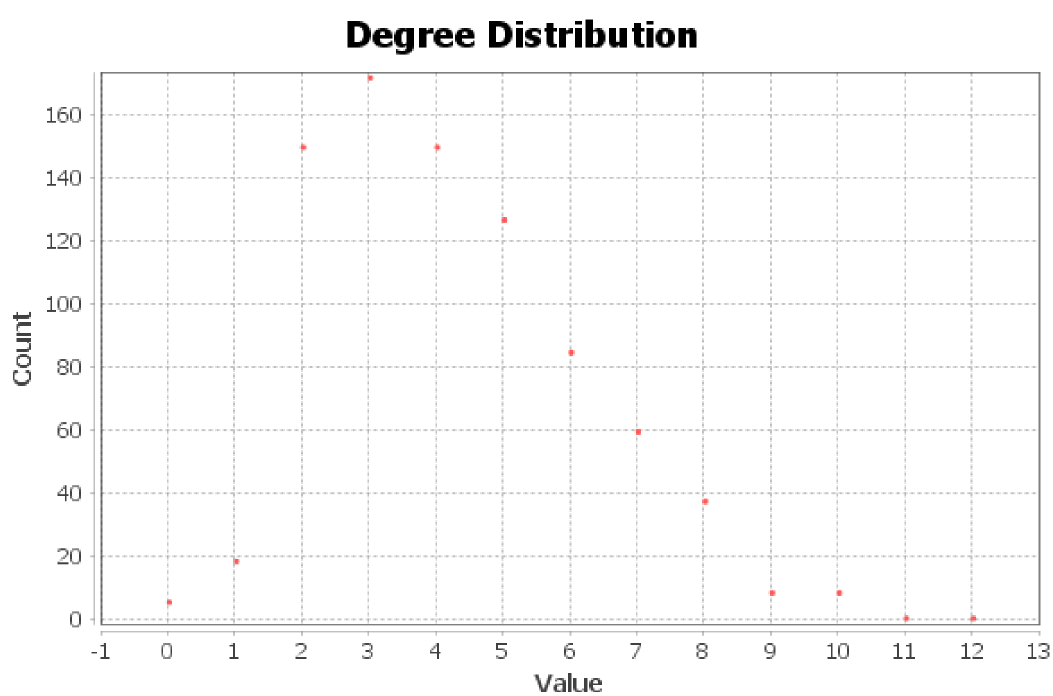


Figure 4.2.2.3. Degree distribution of Dataset 03

4.2.3 Weighted degree distribution

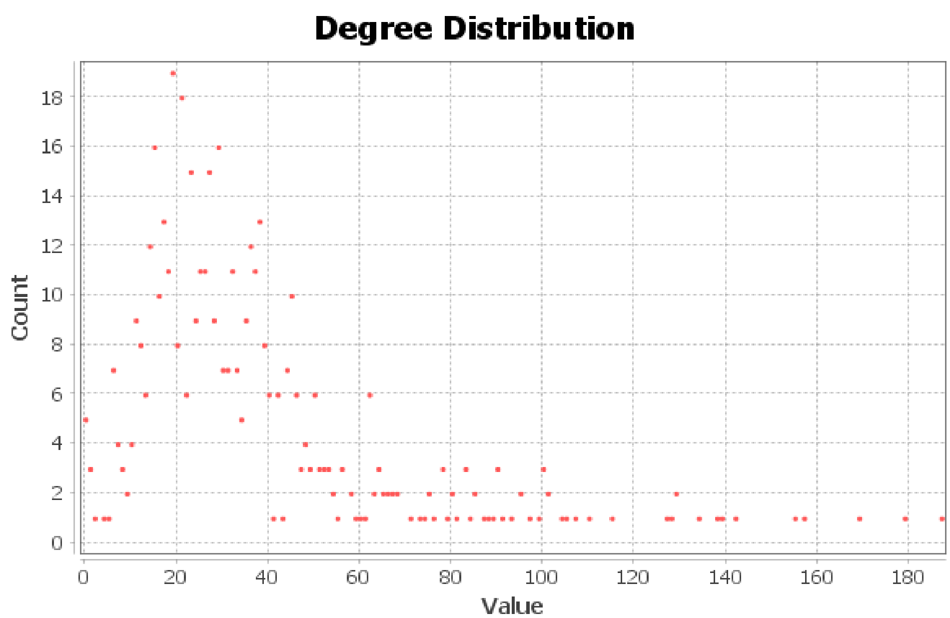


Figure 4.2.3.1. W-degree distribution of Dataset 01

Dataset 01 has a weighted average degree of 37.031 as we can see from the figure 4.2.3.1 that almost one third of the nodes has a very higher weighted degree which is somewhat around 6 to 18 ranges. Although two third of the nodes has a very lower weighted degree, that means vehicles corresponding to that node mostly connected with its neighbor in a congested area which indicates that, two third of the vehicles are somewhat in the middle of a jam.

The degree distribution of dataset 02 has been showed in figure 4.2.3.2 as we can see that it has around 31.393 weighted average degree and dataset 03 has a very high weighted average degree that is 51.807 which is quite larger than the dataset 01 and dataset 03.

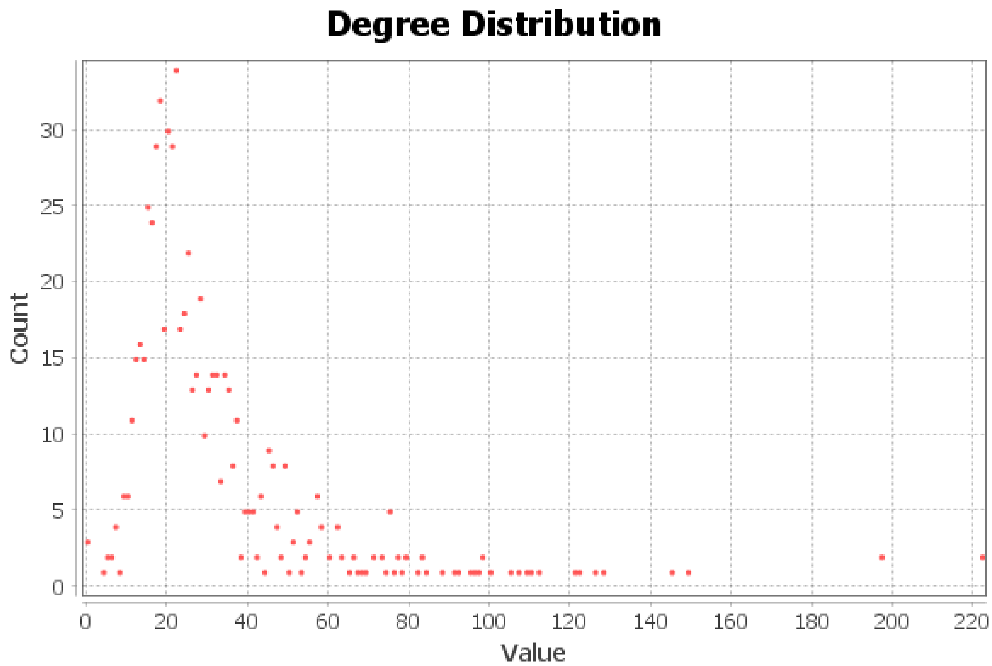


Figure 4.2.3.2. W-degree distribution of Dataset 02

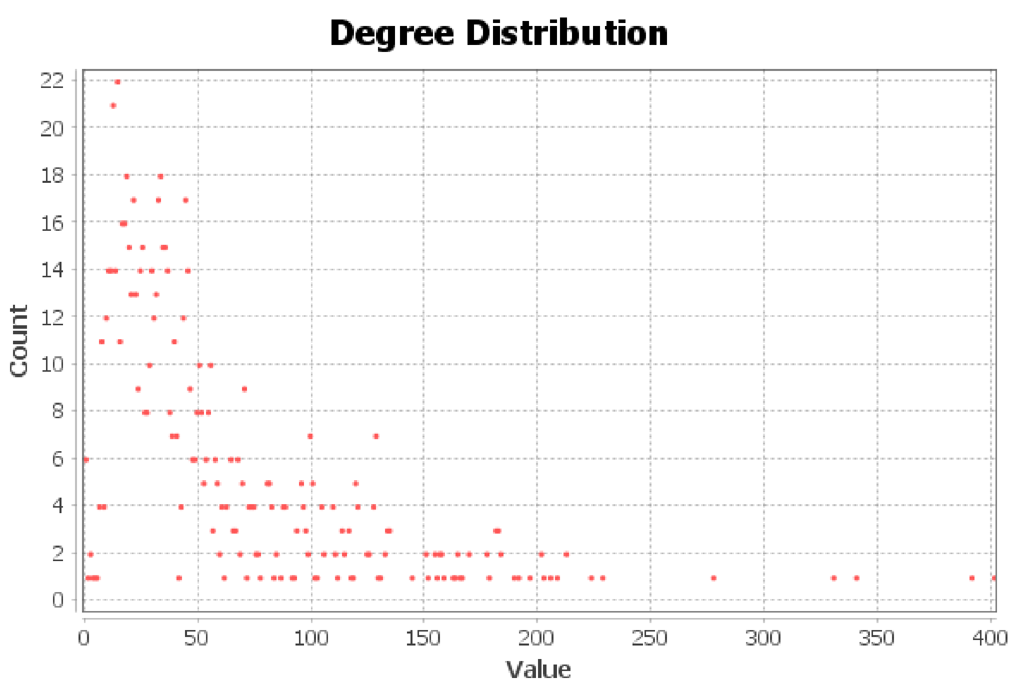


Figure 4.2.3.3. W-degree distribution of Dataset 03

4.2.4 Community size distribution

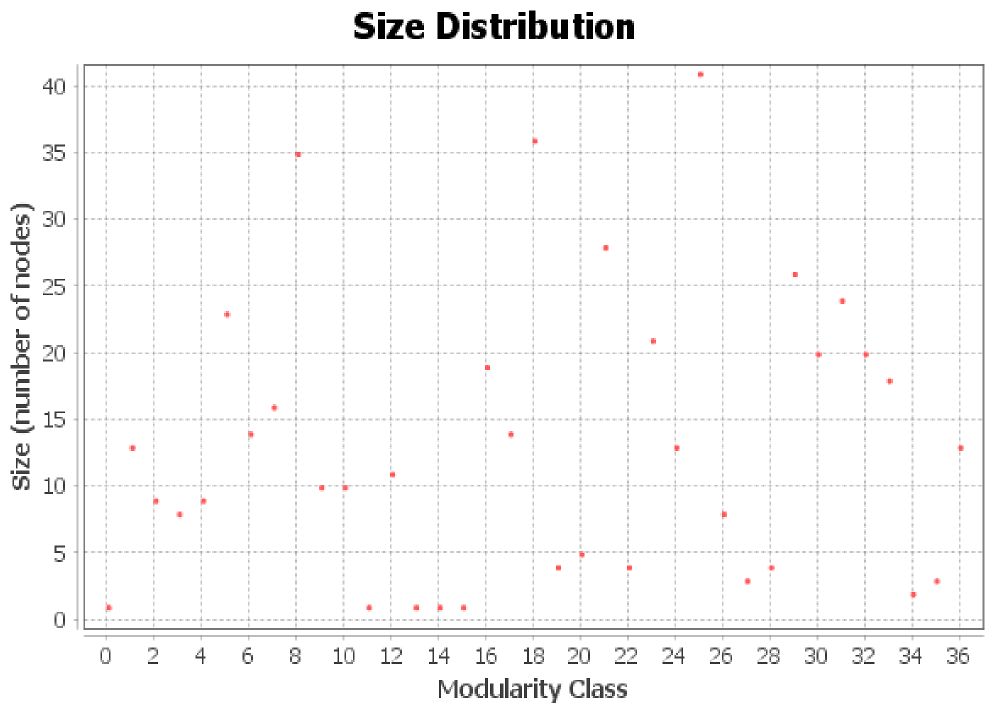


Figure 4.2.4.1. Communities size distribution of Dataset 01

Figure 4.2.4.1 shows that there are 37 modular class in the network. Among them the lowest no of nodes a module holds is less than 5 and the highest no of nodes a module holds is 40 nodes. The community size distribution has an average of 37 of modular class in total. Figure 4.2.4.2 show the communities size distributions of dataset 02 where we can see that total 38 no of modular class exists and the highest no of node a module hold is 30 whereas the lowest no of node any module hold is 1. Three module hold only one node in their community. Figure 4.2.4.3 shows the communities size distributions for dataset 03 where there are total 40 no of modular class in the graph.

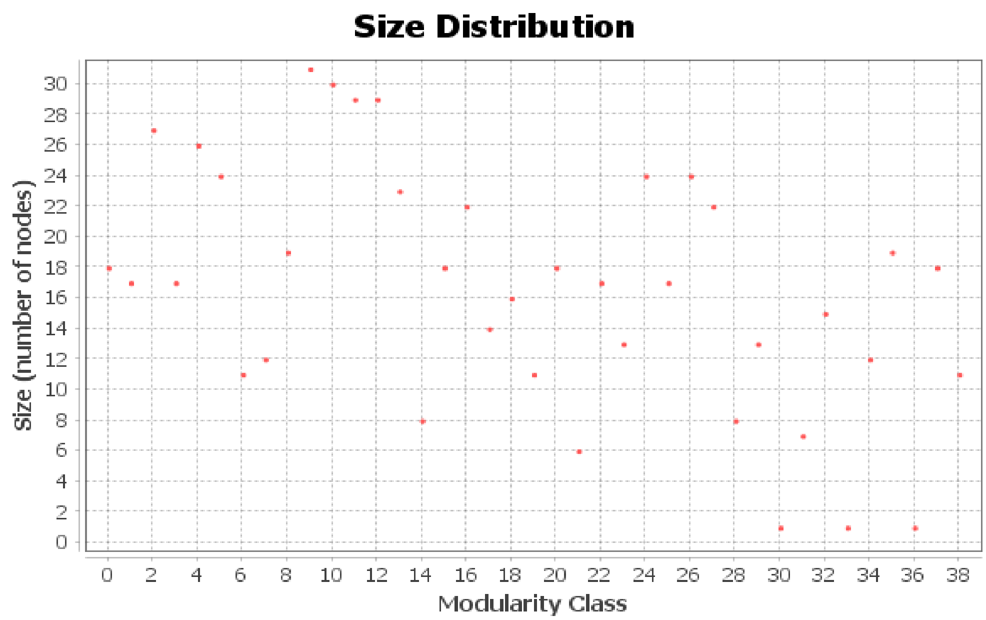


Figure 4.2.4.2. Communities size distribution of Dataset 02

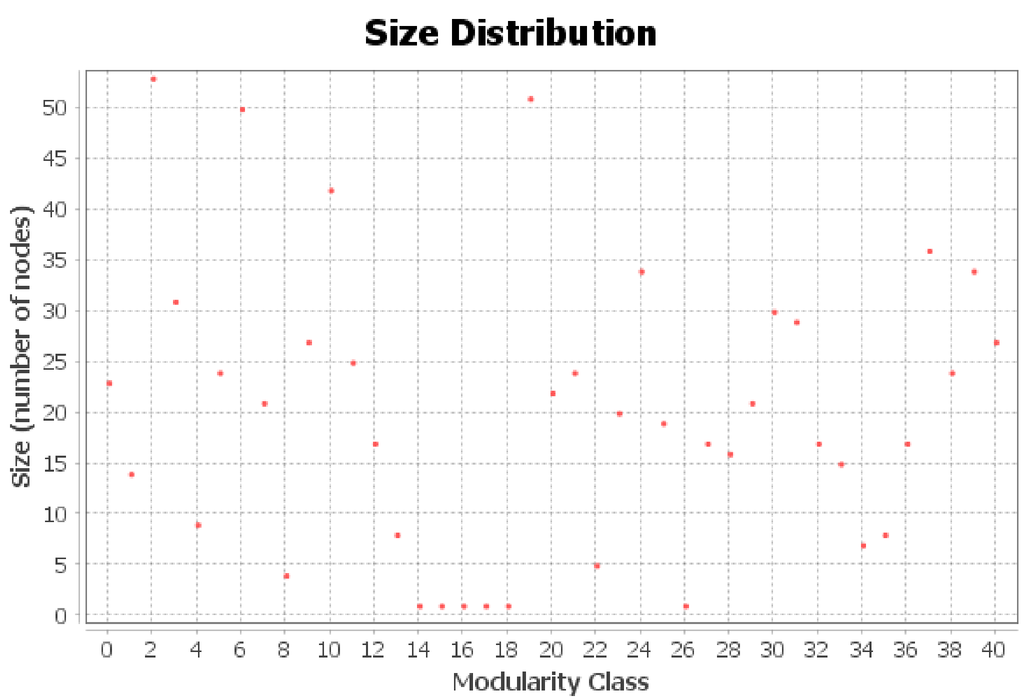


Figure 4.2.4.3. Communities size distribution of Dataset 03

4.2.5 Ecentricity distribution

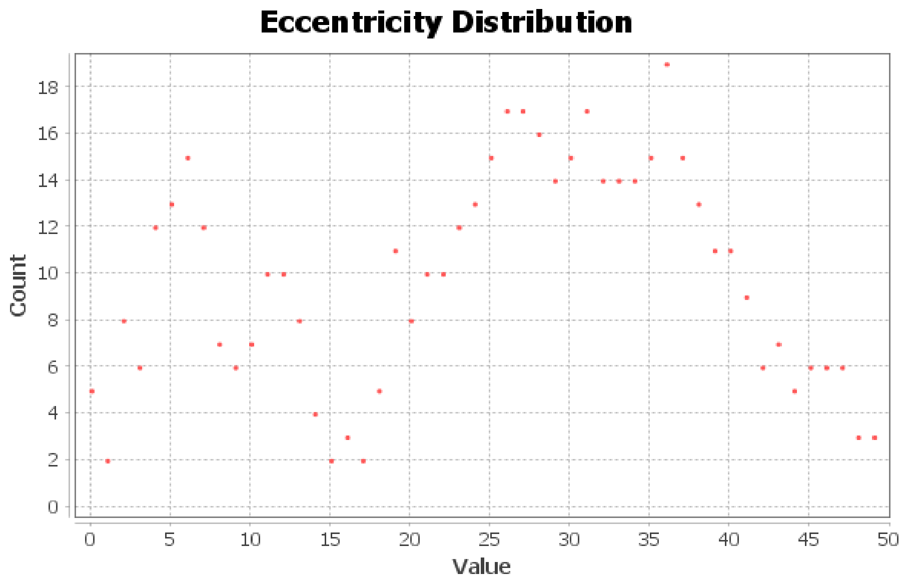


Figure 4.2.5.1. Eccentricity distribution of Dataset 01

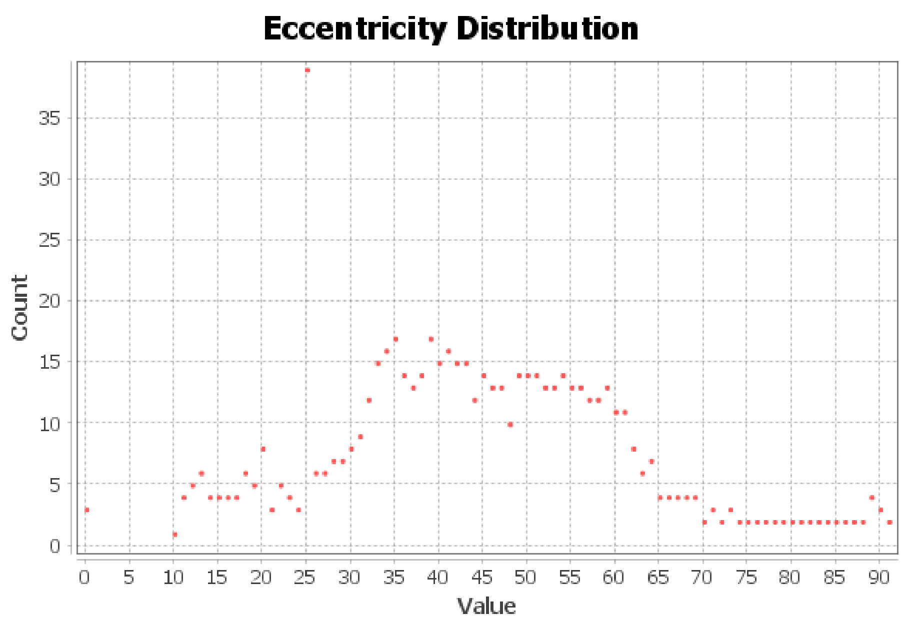


Figure 4.2.5.2. Eccentricity distribution of Dataset 02

Figure 4.2.5.1, 4.2.5.2 and 4.2.5.3 shows the eccentricity distribution of dataset 01, 02 and 03 respectively.

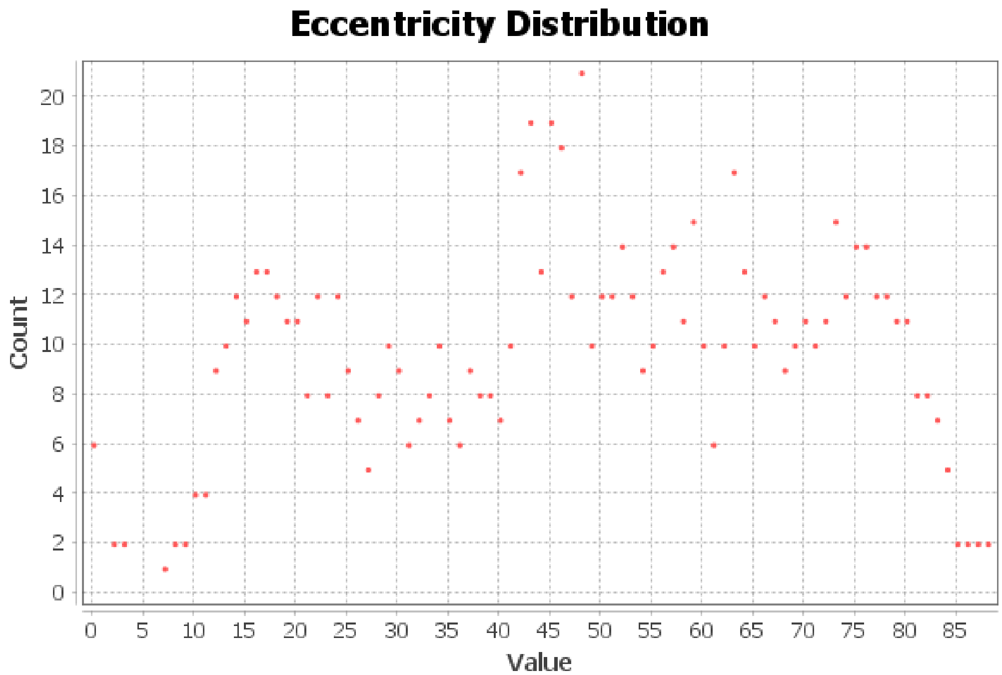


Figure 4.2.5.3. Eccentricity distribution of Dataset 03

4.2.6 An integrated table with key network properties

Table 4.2.6. An integrated table with network properties of three datasets.

Network Properties	Dataset 01 (Google Maps)	Dataset 02 (Bing Maps)	Dataset 03 (Yahoo Maps)
Average Clustering Coefficient	**0.334**	**0.306**	**0.441**
Total triangles	**321**	**406**	**1227**

Average Degree	**3.072**	**3.011**	**4.230**
Average Weighted Degree	**37.031**	**31.393**	**51.807**
Number of Weakly Connected Components	**22**	**12**	**17**
Graph Density	**0.006**	**0.005**	**0.005**
Modularity	**0.942**	**0.951**	**0.948**
Modularity with resolution	**0.942**	**0.951**	**0.948**
Number of Communities	**37**	**39**	**41**
Network Diameter	**49**	**91**	**88**
Average Path Length	**13.387**	**21.253**	**24.788**

4.3 Regression analysis

We have found some key network properties from three different dataset. Using these information from different datasets, we have generated a new dataset that includes all the network properties of three different datasets. Using the new generated dataset, we have run several regression to find

obs.	totalNodes	pcarNodes	avgClustCoeff	avgDegree	avgWeightDegree	weeklyConnComp
1	489	266	0.334	3.072	37.031	22
2	649	502	0.306	3.011	31.393	12
3	827	734	0.441	4.13	51.807	17

graphDensity	modularity	totalCommunity	networkDiameter	avgPathLength
0.006	0.942	37	49	13.387
0.005	0.951	39	91	21.253
0.005	0.948	41	88	24.788

Figure 4.3.1. Dataset for regression on network properties of three datasets

relations between the densities of private car in the network with other network properties. We have run regression of private car on average degree, on average weighted degree, on weekly connected components, on graph density, on modularity, on total number of community in the network, on network diameter and on average path length.

. reg pcarNodes avgDegree

Source	SS	df	MS
Model	76922.1387	1	76922.1387
Residual	32592.528	1	32592.528
Total	109514.667	2	54757.3333

Number of obs =	3
F(1, 1) =	2.36
Prob > F =	0.3673
R-squared =	0.7024
Adj R-squared =	0.4048
Root MSE =	180.53

pcarNodes	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
avgDegree	311.6966	202.8922	1.54	0.367	-2266.293	2889.686
_cons	-560.4523	698.5329	-0.80	0.570	-9436.154	8315.249

Figure 4.3.2. Regression of amount of private cars on average degree of the network

These regression gave us some interesting relationship and from using the regression result we can easily interpret the presence of how huge amount of private car can affect the overall network structure.

From figure 4.3.2 we can see that, presence of almost 311 private car can increment the average degree of a network by one. And the intercept coefficient is telling us, if we remove 560 no of private car from an existing network, the average degree of the network will be zero. If we test the hypothesis at 5% significance level, we won't be able to reject the null hypothesis that, private car do not have any effect on the average degree of the network. In the next part we have shown the regression between the amount of private cars in the street and the average weighted degree of the whole network topology.

```
. reg pcarNodes avgWeightDegree
```

Source	SS	df	MS
Model	53243.3562	1	53243.3562
Residual	56271.3105	1	56271.3105
Total	109514.667	2	54757.3333

Number of obs =	3
F(1, 1) =	0.95
Prob > F =	0.5088
R-squared =	0.4862
Adj R-squared =	-0.0276
Root MSE =	237.22

pcarNodes	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
avgWeightDegree	15.47675	15.91074	0.97	0.509	-186.6884	217.6419
_cons	-119.595	652.197	-0.18	0.885	-8406.543	8167.353

Figure 4.3.3. Regression of amount of private cars on average weighted degree of the network

From figure 4.3.3 we can see that, amount of private car in the network has an average of 1/15.47 impact factor on the average weighted degree of the network.

The t test has given us a negative value for the intercept coefficient. That means if we remove around 119 private cars from the network, the networks average weighted degree becomes zero.

That means the network become less congested and it can predict that, these network is easier for transports to move on.

```
. reg pcarNodes weeklyConnComponent

      Source |       SS       df       MS              Number of obs =       3
-------------+------------------------------           F(  1,     1) =    0.34
       Model |       27848     1       27848           Prob > F      =  0.6635
    Residual |  81666.6667     1  81666.6667           R-squared     =  0.2543
-------------+------------------------------           Adj R-squared = -0.4914
       Total |  109514.667     2  54757.3333           Root MSE      =  285.77

------------------------------------------------------------------------------
          pcarNodes |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------------+---------------------------------------------------------
weeklyConnComponent |      -23.6   40.41452    -0.58   0.664    -537.1152    489.9152
              _cons |   901.8667   706.5802     1.28   0.423    -8076.086    9879.819
------------------------------------------------------------------------------
```

Figure 4.3.4. Regression of amount of private cars on weakly connected components of the network

Figure 4.3.4 shows the relationship between amount of private car in a network and the amount of weekly connected component. From the result of regression analysis we can say that, weekly connected component is negatively connected with the amount of private car in the topology.

```
. reg pcarNodes graphDensity

      Source |       SS       df       MS              Number of obs =       3
-------------+------------------------------           F(  1,     1) =    3.07
       Model |  82602.6667     1  82602.6667           Prob > F      =  0.3302
    Residual |       26912     1       26912           R-squared     =  0.7543
-------------+------------------------------           Adj R-squared =  0.5085
       Total |  109514.667     2  54757.3333           Root MSE      =  164.05

------------------------------------------------------------------------------
   pcarNodes |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
graphDensity |    -352000   200917.9    -1.75   0.330     -2904904     2200904
       _cons |       2378    1075.74     2.21   0.270    -11290.57    16046.57
------------------------------------------------------------------------------
```

Figure 4.3.5. Regression of amount of private cars on graph density of the network

From the example we can see that, if 23 private car leaves the network making it a less congested, then the network will have one more weekly connected component. That means the network will be distributed with vehicles. Less vehicles will be hanging around in the same area.

. reg pcarNodes modularity

Source	SS	df	MS
Model	47470.0952	1	47470.0952
Residual	62044.5714	1	62044.5714
Total	109514.667	2	54757.3333

Number of obs =	3
F(1, 1) =	0.77
Prob > F =	0.5425
R-squared =	0.4335
Adj R-squared =	-0.1331
Root MSE =	249.09

pcarNodes	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
modularity	33619.05	38435.03	0.87	0.542	-454744.3	521982.4
_cons	-31336.57	36398.26	-0.86	0.547	-493820.3	431147.2

Figure 4.3.6. Regression of amount of private cars on modularity of the network

Figure 4.3.6 shows the regression analysis between the most amount of vehicle in the network, private car and the modularity in the network. Modularity is a very important property of a complex network as modularity can say a lot about a network. From the analysis we can see that, if 33619 amount of private car can be added in a network the modularity of the complex network will be increased by one. Moreover looking at the intersect we can understand that, if we can decrease 33619 amount of private cars from a network the modularity could be zero. That means, adding private cars will decrease module numbers in the network by a huge amount.

```
. reg pcarNodes totalCommunity

      Source |       SS       df       MS              Number of obs =       3
-------------+------------------------------           F(  1,      1) =41067.00
       Model |      109512     1      109512           Prob > F      =  0.0031
    Residual |  2.66666667     1  2.66666667           R-squared     =  1.0000
-------------+------------------------------           Adj R-squared =  1.0000
       Total |  109514.667     2  54757.3333           Root MSE      =   1.633

------------------------------------------------------------------------------
   pcarNodes |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
totalCommunity |      117   .5773503   202.65   0.003     109.6641    124.3359
       _cons |  -4062.333   22.53639  -180.26   0.004    -4348.685   -3775.981
------------------------------------------------------------------------------

.
```

Figure 4.3.7. Regression of amount of private cars on total community of the network

Figure 4.3.7 shows us the regression between the private car amount and total community in the network. The result is really interesting as it suggests us that, one increase in community will be led by 117 amount of increment of private cars in the street of that particular network. And to make total number of community almost zero, almost all the private car must be removed from the network.

The result is meaning full, we have already witnessed by our network analysis from section 4.1 that, most the vehicles that are guilty behind causing extremely stand still situations on the way is private cars.

Moreover they are responsible for creating giant component in the network. Although the standard error of the intercept is quite large but as an empirical analysis we can assume that this value has quiet an impact on the network.

. reg pcarNodes networkDiameter

Source	SS	df	MS
Model	76350.0328	1	76350.0328
Residual	33164.6339	1	33164.6339
Total	109514.667	2	54757.3333

Number of obs	= 3
F(1, 1)	= 2.30
Prob > F	= 0.3710
R-squared	= 0.6972
Adj R-squared	= 0.3943
Root MSE	= 182.11

pcarNodes	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
networkDiameter	8.338798	5.49587	1.52	0.371	-61.49285	78.17044
_cons	-133.082	430.7163	-0.31	0.809	-5605.852	5339.688

Figure 4.3.8. Regression of amount of private cars on network diameter of the network

The figure 4.3.8 and figure 4.3.9 sows relations between amount of private car with the network diameter and with the average path length.

. reg pcarNodes avgPathLength

Source	SS	df	MS
Model	104712.234	1	104712.234
Residual	4802.43242	1	4802.43242
Total	109514.667	2	54757.3333

Number of obs	= 3
F(1, 1)	= 21.80
Prob > F	= 0.1343
R-squared	= 0.9561
Adj R-squared	= 0.9123
Root MSE	= 69.3

pcarNodes	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
avgPathLength	39.20747	8.396548	4.67	0.134	-67.48078	145.8957
_cons	-276.0072	171.0745	-1.61	0.353	-2449.715	1897.7

Figure 4.3.9. Regression of amount of private cars on average path length of the network

Chapter 5

Conclusions

The concept of Social Internet of Things could be applied in many domains. We applied heuristics and concepts of SIOT to convert the traffic domain in a complex network domain. Using network properties and tools we have analyzed the complex network and extract different characteristics of traffic behavior in Bijay Sarani. Lastly, using extracted information we have run regression and found relationship among the amount of private cars on the network and different network properties of the complex network. We have come to a conclusion that private cars are the most terrific reasons for traffic congestions and giant component in Bijay Sarani.

We have manually collected dataset from three different satellite view of Bijay Sarani. Only three dataset is not enough for our further analysis. For that reason, we will use live traffic update from google map. Using particular congestion indication from their map, we will extract raw information using computer vision library of Matlab. Then using our algorithm that has been developed upon characteristics and heuristics of Social Internet of things, we will generate some pretty good amount of synthesized dataset that will reflect the traffic condition of Bijay sarani in different times of a day. Once we get the synthesized dataset we can run our further analysis like Multiple Regression, Ordinary least square analysis. From that analysis we hope that we will be able to provide a generalized model that will describe pattern and probability of traffic congestion in Bijoy sarani.

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