RESILIENCE OF DELHI ROAD NETWORKS TO TRAFFIC DISRUPTIONS

BY

M. SATYA SAI TEJA (Enrolment No. 20/11/EC/011)

VAIBHAV TRIPATHI (Enrolment No. 20/11/EC/018)

under the guidance of

Dr. Krishnan Rajkumar, School of Engineering JNU, Delhi

in the partial fulfilment of the requirements
for the award of the degree of

Bachelor of Technology

School of Engineering

Jawaharlal Nehru University, New Delhi

December, 2023

JAWAHARLAL NEHRU UNIVERSITY
SCHOOL OF ENGINEERING

DECLARATION

We declare that the project work entitled **"RESILIENCE OF DELHI ROAD NETWORKS TO TRAFFIC DISRUPTIONS"** which is submitted by us in partial fulfilment of the requirements for the award of the **Bachelor of Technology** (part of Five-Year Dual Degree Course) in **Computer Science Engineering** to the School of Engineering, Jawaharlal Nehru University, Delhi comprises only our original work, and due acknowledgement has been made in the text to all other materials used.

M. Satya Sai Teja

Vaibhav Tripathi

JAWAHARLAL NEHRU UNIVERSITY
SCHOOL OF ENGINEERING

CERTIFICATE

This is to certify that the project work entitled **"RESILIENCE OF DELHI ROAD NETWORKS TO TRAFFIC DISRUPTIONS"** being submitted by **Mr. M. Satya Sai Teja** (Enrolment No. 20/11/EC/011) in fulfilment of the requirements for the award of the **Bachelor of Technology** (part of Five-Year Dual Degree Course) in **Computer Science Engineering**, will be carried out by him under my supervision.

In my opinion, this work fulfils all the requirements of an Engineering Degree in respective streams as per the regulations of the School of Engineering, Jawaharlal Nehru University, Delhi. This thesis does not contain any work, which has been previously submitted for the award of any other degree.

Dr. Krishnan Rajkumar
(Supervisor)
Assistant Professor
School of Engineering
Jawaharlal Nehru University, Delhi

JAWAHARLAL NEHRU UNIVERSITY
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Dr. Krishnan Rajkumar
(Supervisor)
Assistant Professor
School of Engineering
Jawaharlal Nehru University, Delhi

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M. Satya Sai Teja

Vaibhav Tripathi Vaibhav

ABSTRACT

Road networks, crucial for the efficient movement of people and goods, often face disruptions due to accidents, natural disasters, and infrastructure failures, impacting societies and economies. This project utilises network science to assess the resilience of road networks, with a focus on their structural characteristics and strategies to enhance robustness. By leveraging data from Open Transit Data - Delhi and other sources, the study employs a comprehensive methodology.

The project contributes to a nuanced understanding of network science factors, offering strategies to fortify existing networks and design more resilient road networks for the future.

LIST OF CONTENTS

CHAPTER 1
INTRODUCTION AND THESIS OVERVIEW

1.1 INTRODUCTION

This thesis employs a network science approach to assess road network resilience. Starting with data collection, we analyse network structure, simulate disruptions, and measure post-disruption performance. Our study enhances understanding of network science and provides insights for urban planning recommendations.

1.2 THESIS OVERVIEW

The primary objective of this thesis is to scrutinise and comprehend the resilience of road networks by employing the tools and methodologies of network science. Through rigorous analysis, the aim is to unravel the underlying factors contributing to network robustness, thereby providing insights that can inform strategies for enhancing the resilience of existing road networks and the design of future road infrastructure.

1.3 ORGANISATION OF CHAPTERS

To achieve a coherent exploration of road network resilience, this thesis is structured as follows:

- Chapter 2: Literature Survey

Provides a comprehensive review of existing literature related to road network resilience, disruption scenarios, and the application of network science in understanding complex systems.

- Chapter 3: Proposed Work and Methodology

Details the methodology employed in this study, including the collection of road maps and public road data, network analysis techniques, simulation of disruption scenarios, and the evaluation of robustness metrics.

- Chapter 4: Result Discussion

Presents the findings from the network structure analysis, disruption scenarios impact assessment, and evaluation of robustness metrics. Each sub-section delves into specific aspects of the analysis, providing a nuanced understanding of the road network resilience.

- Chapter 5: Conclusion

Summarises the key findings, their implications, and recommendations for practical applications. Additionally, this chapter discusses the limitations of the study and proposes avenues for future research in the domain of road network resilience.

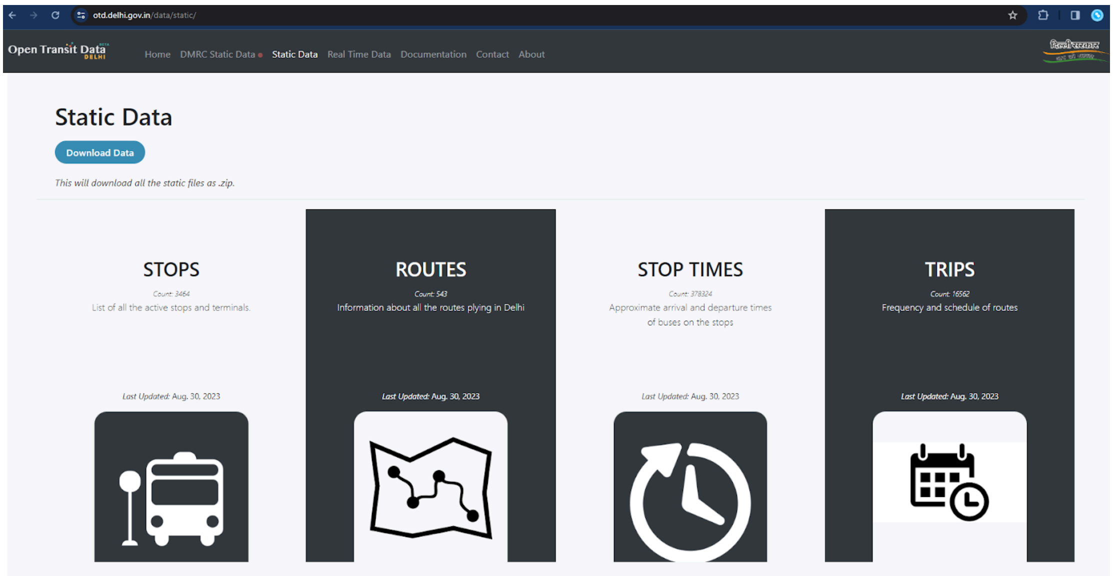
CHAPTER 2
LITERATURE SURVEY

2.1 INTRODUCTION

The literature review explores the resilience of road networks, specifically focusing on Delhi, with insights from Tamene Sinishaw Gelaye's research on Addis Ababa's road network. Gelaye assessed network resilience using the open street map format, while our study employs the GTFS format for Delhi. Both investigations aim to understand the robustness of urban road networks in the face of traffic disruptions. By building upon Gelaye's work and adapting methodologies to the unique context of Delhi, we contribute to the broader understanding of road network resilience and its implications for urban transportation systems.

2.2 DATASET

In this project, we use data mainly from Open Transit Data - Delhi, along with information from other relevant sources. This big dataset is the core of our investigation, giving us useful insights into how Delhi's transit system works. Open Transit Data - Delhi is like a treasure trove, providing details about routes, stops, and schedules, which helps us take a close look at the city's public transportation network. Our method uses this data to carefully study how well the road network can handle disruptions, how efficient it is, and how adaptable it can be. By bringing in information from various sources, our study makes sure we have a full understanding of how things work in Delhi's transit system. This helps us explore network resilience in a detailed and informed way.



2.3 NETWORK SCIENCE IN ROAD NETWORKS

In this project, we explore the world of network science within the context of road networks. Network science helps us understand how different parts of the road network are connected and how information or disruptions can flow through these connections. Think of it like understanding the relationships and interactions between various roads, intersections, and stops in a city. By applying network science to road networks, we aim to unravel the complexities of Delhi's transportation system. This involves studying how disruptions, such as road closures or accidents, impact the overall network and how resilient the system is in bouncing back from these challenges. Through this approach, we gain valuable insights into the structure, efficiency, and adaptability of Delhi's road network, contributing to a deeper understanding of how these networks function in real-world scenarios.

CHAPTER 3
PROPOSED WORK AND METHODOLOGY

3.1 DATA COLLECTION

To conduct a comprehensive network analysis, we needed access to the transit data related to the road network in Delhi. Our search led us to the Open Transit Delhi website, where we found a wealth of information, encompassing both static and dynamic data. We downloaded the static data of the road network, which was in GTFS (General Transit Feed Specification) format and contained information such as public transportation schedules and associated geographic information.

3.2 NETWORK ANALYSIS

After obtaining the transit data, we chose to create a Python script. Utilising the features of the Python programming language, we extensively employed the robust networkx library, well-regarded in network science projects. Our initial efforts concentrated on data preprocessing, excluding irrelevant fields from our analysis. To improve accessibility, we structured the data into dictionaries.

- **3.2.1 Directed Graph**

We constructed a directed graph where nodes symbolise stops and edges represent the connecting roads. Subsequently, we endowed the nodes with various attributes, including stop ID, stop name, latitude, longitude, in-degree, out-degree, and overall degree. The degree of each node corresponds to the cumulative number of trips associated with the stop.

Furthermore, the edges were enriched with attributes such as distance, along with a dictionary encapsulating route IDs and trip IDs. To facilitate computation, the initial distance between two stops was set to zero.

- **3.2.2 Degree Distribution**

Degree distribution in a network reveals how connections are spread among nodes. It's a statistical measure defining the likelihood that a randomly chosen node has a specific number of connections. Understanding degree distribution helps unveil key network properties like connectivity and robustness. Two common types of degree distribution are Normal Distribution and Power-law Distribution.

- **3.2.3 Power Law Distribution**

Power-law distribution describes how connections are distributed in a way that a small number of elements have a large number of connections, while most have only a few. It is often observed in various networks and signifies that a small number of nodes play a critical role. The power law distribution equation is represented as:

$$(p_k \sim k^{-\alpha})$$

In this equation pk is the probability that a randomly selected node has a degree k and alpha is the power exponent. Presence of power law distribution often leads to the emergence of scale free property in networks.

- **3.2.4 Scale Free Property**

In a scale-free network, most nodes have only a few connections, but a few hubs have a lot. This uneven distribution creates a hierarchy where a small number of nodes are crucial for the network's integrity. While scale-free networks are resilient to random failures, they're sensitive to targeted attacks on these highly connected hubs.

- **3.2.5 Hubs**

Network hubs, identified by their high node degree centrality, play a key role in influencing connectivity and information flow. Node degree centrality measures a node's importance based on its connections. The concept of hubs relates to a power-law distribution, emphasizing nodes with high degrees. The centrality of a node (i) in a network is represented as:

$$C_i = \frac{\{\text{Degree of Node }\}i}{\{\text{Maximum Degree in the Network}\}}$$

This equation provides a normalised measure of how central a node is based on its degree.

- **3.2.6 Betweenness Centrality**

Betweenness centrality measures how important a node is in helping information or influence move around a network. Nodes with high betweenness centrality have a big impact on how other nodes communicate or interact. It's calculated by looking at the number of shortest paths that go through a node compared to the total paths in the network. Nodes with high betweenness often act as important bridges or bottlenecks, controlling how information flows between different parts of the network.

3.3 DISRUPTION SCENARIOS

We simulate disruptions, such as road closures, malignant accidents, natural disasters and assess their impact on network connectivity. Visualize the network both before and after the disruption to clearly illustrate the resulting changes.

- **3.3.1 Road Closure**

Road closures, stemming from construction, maintenance, or infrastructure projects, constitute prolonged disruptions lasting from days to years. To simulate such disruptions, we will selectively remove edges associated with nodes in the network.

- **3.3.2 Malignant Accidents**

Road accidents can temporarily close specific routes, leading to the temporary cancellation of trips to stops along the affected route. To simulate such disruptions, we remove trips associated with the stops connecting the impacted route.

- **3.3.3 Natural Disasters**

Natural disasters exhibit varying durations and impacts on road networks. Brief disruptions, such as heavy rains, lead to temporary delays in trips. In contrast, prolonged events like floods can endure for days, causing road closures, rendering certain stops inaccessible, and necessitating the cancellation of all trips along affected routes. To simulate such disruptions, we remove nodes, rendering corresponding locations inaccessible.

3.4 ROBUSTNESS METRICS

Robustness refers to the ability of a network to maintain its structural and functional integrity in the face of perturbations, disruptions, or attacks. Specifically, degree-based robustness metrics provide insights into how well a network can withstand the removal of nodes or edges based on their degrees. In order to understand it better first let us look at the Average degree and Standard Deviation.

- **3.4.1 Average Degree**

The average degree of a network is calculated by summing the degrees of all nodes and dividing by the total number of nodes. A higher average degree indicates a denser network, suggesting stronger connectivity among nodes. In terms of robustness, networks with higher average degrees tend to be more resilient to random failures.

- **3.4.2 Standard Deviation of Degree**

The standard deviation of degree measures the degree variability among nodes in the network. A higher standard deviation suggests a more heterogeneous network where nodes have diverse degrees. In terms of robustness, networks with higher degree heterogeneity may exhibit a scale-free structure, making them more resistant to targeted attacks on highly connected nodes.

Networks with a high average degree are generally more robust to random failures because the removal of a few nodes is unlikely to significantly impact overall connectivity. Networks with a high degree standard deviation may exhibit a scale-free topology, where a few nodes (hubs) have much higher degrees than the rest. While such networks are vulnerable to targeted attacks on hubs, they often have a higher tolerance to random failures.

3.5 RECOVERY STRATEGIES

Recovery strategies play a crucial role in ensuring the resilience and efficient functioning of transportation systems. Recovery strategies involve the planning and execution of actions to mitigate the impact of disruptions, minimize recovery time, and restore normal traffic flow.

- **3.5.1 Degree Distribution**

Establishing alternative routes and diversions helps redirect traffic away from affected areas, spreading the load and preventing gridlock. Providing clear signage and real-time information to drivers about alternative routes minimizes delays and improves overall network resilience.

- **3.5.2 Investment in Infrastructure Resilience**

Building and maintaining resilient infrastructure, such as durable road materials and robust bridges, enhances the network's ability to withstand and recover from disruptions. Investing in resilient infrastructure reduces the frequency and severity of disruptions, contributing to the long-term sustainability of the road network.

Recovery strategies are integral components of road network resilience, ensuring the swift and effective response to disruptions. By combining early detection, dynamic traffic management, alternative routing, collaboration, and resilient infrastructure, transportation authorities can enhance the recovery process and minimize the impact of disruptions on road networks. These strategies contribute to the overall resilience and sustainability of urban transportation systems, ensuring smooth traffic flow and improved safety for all road users.

3.6 URBAN PLANNING

In this section we aim to fortify Delhi's road transportation network, particularly focusing on enhancing resilience during unforeseen disasters. Employing analytical tools and strategic algorithms, our approach is rooted in understanding the critical nodes of the road network, ensuring that the city is prepared for disruptions caused by accidents, natural disasters, or infrastructure failures.

It begins with a detailed network analysis, delving into the topological properties such as betweenness centrality, to identify key hubs that significantly influence traffic dynamics. By understanding the structural and functional importance of these nodes, we lay the foundation for targeted interventions to strengthen the overall network. Through a systematic and data-driven approach, we envision a city that is not only responsive to unforeseen events but also strategically positioned for long-term sustainability and adaptability.

CHAPTER 4
RESULT DISCUSSION

4.1 ANALYSIS OF NETWORK STRUCTURE

We present the findings of our network analysis in distinct sections below.

- ### 4.1.1 Construction of a Directed Graph

We constructed a directed graph and assigned some attributes to its nodes and edges.

```
In [7]: # Create a directed graph
G = nx.DiGraph()

# Insert Nodes
for index, row in stops.iterrows():
    stop_id = row['stop_id']+
    G.add_node(stop_id, type='stop', stop_name=row['stop_name'], stop_lat=float(row['stop_lat']), stop_lon=float(row['stop_lon'])

# Insert Edges
prev_trip_id = None
prev_stop_id = None
prev_stop_seq = 0

for _, row in stop_times.iterrows():
    cur_trip_id = row['trip_id']
    cur_stop_id = row['stop_id']
    cur_stop_seq = int(row['stop_sequence'])

    if prev_stop_id is not None:
        if prev_trip_id == cur_trip_id:
            if (prev_stop_seq + 1) == cur_stop_seq:
                if prev_stop_id != cur_stop_id:
                    route_id = trip_to_route[cur_trip_id]
                    if G.has_edge(prev_stop_id, cur_stop_id):
                        if route_id in G[prev_stop_id][cur_stop_id]['trip_dict']:
                            G[prev_stop_id][cur_stop_id]['trip_dict'][route_id] += (cur_trip_id,)
                        else:
                            G[prev_stop_id][cur_stop_id]['trip_dict'][route_id] = (cur_trip_id,)
                    else:
                        G.add_edge(prev_stop_id, cur_stop_id, trip_dict={route_id: (cur_trip_id,)}, distance=0)
                    G.nodes[prev_stop_id]['out_degree'] += 1
                    G.nodes[prev_stop_id]['degree'] = G.nodes[prev_stop_id]['in_degree'] + G.nodes[prev_stop_id]['out_degree']
                    G.nodes[cur_stop_id]['in_degree'] += 1
                    G.nodes[cur_stop_id]['degree'] = G.nodes[cur_stop_id]['in_degree'] + G.nodes[cur_stop_id]['out_degree']

        else:
            prev_stop_seq = 0
    else:
        prev_stop_seq = 0

    prev_stop_id = cur_stop_id
    prev_trip_id = cur_trip_id
    prev_stop_seq = cur_stop_seq

print("Number of nodes:", G.number_of_nodes())
print("Number of edges:", G.number_of_edges())

Number of nodes: 11205
Number of edges: 23079
```

fig 4.1.1(a)

With 11,205 nodes (Stops) and 23,079 edges, the graph's sheer size makes visualising the entire network challenging. Consequently, we focus on analysing key network science properties within select portions of the network.

```
In [20]: print( len(G[488][233]['trip_dict']))
         print(G[488][233]['trip_dict'][142])
         print( G.nodes[488]['out_degree'])
         print( G.nodes[488]['in_degree'])
         print( G.nodes[488]['degree'])
         print(G.nodes[488])

84
('142_19_53', '142_09_33', '142_14_13', '142_11_53', '142_07_33', '142_16_33', '142_07_53', '142_19_13', '142_12_13', '142_16_1
3', '142_10_13', '142_12_33', '142_18_13', '142_08_13', '142_09_13', '142_08_53', '142_06_53', '142_18_53', '142_10_53', '142_1
8_33', '142_14_53', '142_08_33', '142_13_33', '142_17_33', '142_15_33', '142_11_13', '142_15_13', '142_11_33', '142_19_33', '14
2_16_53', '142_15_53', '142_06_13')
4876
4857
9733
{'type': 'stop', 'stop_name': 'Najafgarh Delhi Gate', 'stop_lat': 28.611746, 'stop_lon': 76.985721, 'in_degree': 4857, 'out_deg
ree': 4876, 'degree': 9733}
```

fig 4.1.1(b)

Referencing figure 4.1.1(b), the image illustrates attribute data for the edge between nodes with stop IDs 488 and 233, along with the attribute data specific to node 488.

- **4.1.2 Degree Distribution**

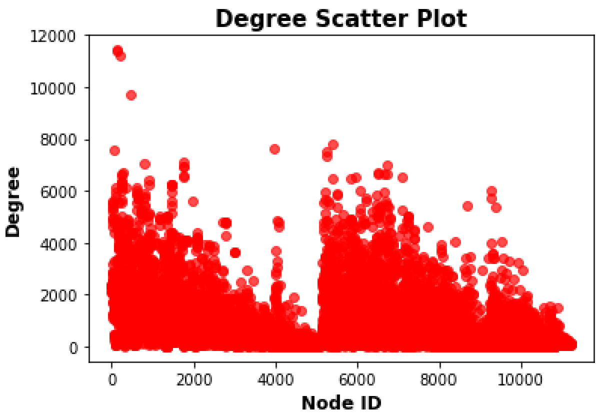


fig 4.1.2(a)

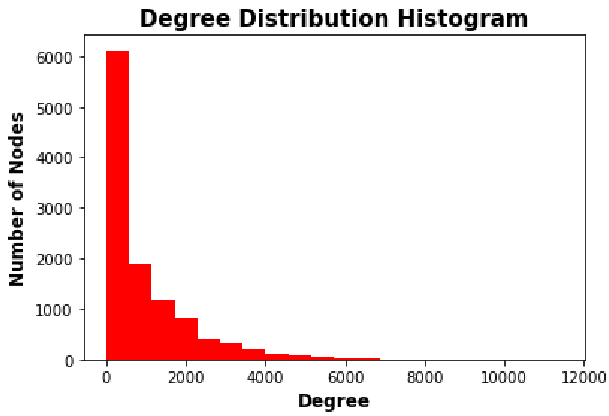


fig 4.1.2(b)

In Figure 4.1.2(a), the scatter plot visually represents the distribution of degrees within our road network graph G. The x-axis corresponds to node IDs (stop IDs), while the y-axis illustrates the degrees of the nodes. Each point on the plot indicates a specific node and its associated degree. Moving to Figure 4.1.2(b), a histogram offers a more detailed view of the degree distribution. This histogram clarifies that the majority of nodes in our graph G possess degrees ranging from 0 to 2000. Here, a node's degree is a straightforward count of the number of trips connected to it. The histogram provides a comprehensive insight into the overall pattern of connectivity within our road network.

- **4.2.2 Power Law Distribution**

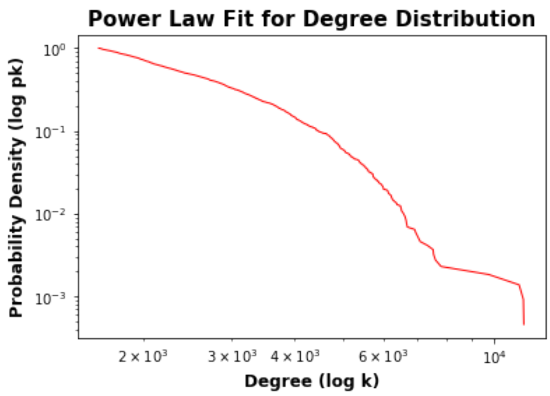


fig 4.2.2(a)

In Figure 4.2.2(a), we used the powerlaw library to study the distribution of node degrees. The alpha value we discovered, 3.08, falls within the typical range for scale-free networks (between 2 and 3). This alpha value suggests that our road network graph exhibits the scale-free property, where a few key places, such as major road junctions, have many connections, while most places have fewer connections. This characteristic makes the road network structure interesting.

- **4.2.3 Hubs**

{'type': 'stop', 'stop_name': 'Health Centre', 'stop_lat': 28.614155, 'stop_lon': 76.985213, 'in_degree': 5717, 'out_degree': 5717, 'degree': 11434}
{'type': 'stop', 'stop_name': 'Jharoda Crossing', 'stop_lat': 28.614413, 'stop_lon': 76.98107, 'in_degree': 5705, 'out_degree': 5705, 'degree': 11410}
{'type': 'stop', 'stop_name': 'Police Station Najafgarh', 'stop_lat': 28.61031861412337, 'stop_lon': 76.9813376578563, 'in_degree': 5595, 'out_degree': 5595, 'degree': 11190}
{'type': 'stop', 'stop_name': 'Najafgarh Delhi Gate', 'stop_lat': 28.611746, 'stop_lon': 76.985721, 'in_degree': 4857, 'out_degree': 4876, 'degree': 9733}
{'type': 'stop', 'stop_name': 'Jahangir Puri Metro Station', 'stop_lat': 28.7273, 'stop_lon': 77.161583, 'in_degree': 3912, 'out_degree': 3912, 'degree': 7824}

fig 4.2.3 (a)

In Figure 4.2.3(a), we depict attribute data related to the top 5 hubs. Notably, the Health Center stop exhibits the highest degree at 11,434 within our network. Moving to Figure 4.2.3(b), you can observe the top 50 hubs, significant bus stops in our graph. Hubs, represented by red nodes, serve as pivotal points with numerous connections. Their significance lies in their ability to link to various routes and trips, making them central in our road network. The arrows between them symbolize bus routes, establishing connections between stops. These hubs play a critical role in Delhi's road network, ensuring seamless connectivity and operational efficiency.

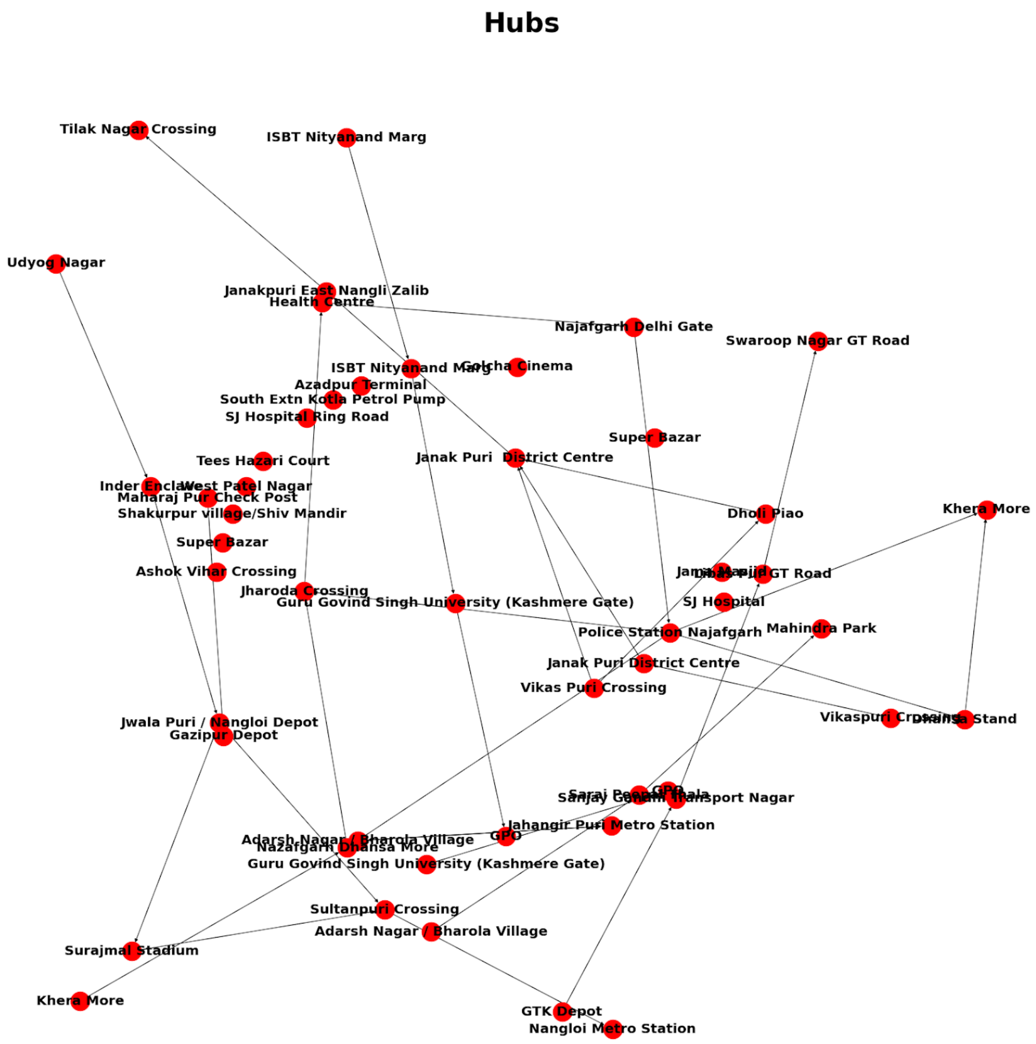


fig 4.2.3(b)

- ### 4.2.4 Betweenness Centrality


```
{'type': 'stop', 'stop_name': 'Aakashwani Bhawan', 'stop_lat': 28.620532, 'stop_lon': 77.210575, 'in_degree': 1801, 'out_degre
e': 1801, 'degree': 3602}
{'type': 'stop', 'stop_name': 'GTK Depot', 'stop_lat': 28.731183, 'stop_lon': 77.158617, 'in_degree': 2257, 'out_degree': 2257,
'degree': 4514}
{'type': 'stop', 'stop_name': 'Roshnara Bagh', 'stop_lat': 28.6733, 'stop_lon': 77.2018, 'in_degree': 1433, 'out_degree': 1433,
'degree': 2866}
{'type': 'stop', 'stop_name': 'Shastri Nagar Metro Station', 'stop_lat': 28.669997, 'stop_lon': 77.181336, 'in_degree': 985, 'o
ut_degree': 985, 'degree': 1970}
{'type': 'stop', 'stop_name': 'Jhandewalan', 'stop_lat': 28.646879, 'stop_lon': 77.204083, 'in_degree': 2802, 'out_degree': 280
2, 'degree': 5604}
```


fig 4.2.4 (a)

In Figure 4.2.4(a), we present attribute data associated with the top 5 nodes exhibiting high betweenness centrality. These nodes function as bridges or bottlenecks within a network, determined by assessing the shortest paths passing through a node in comparison to the total paths in the network.

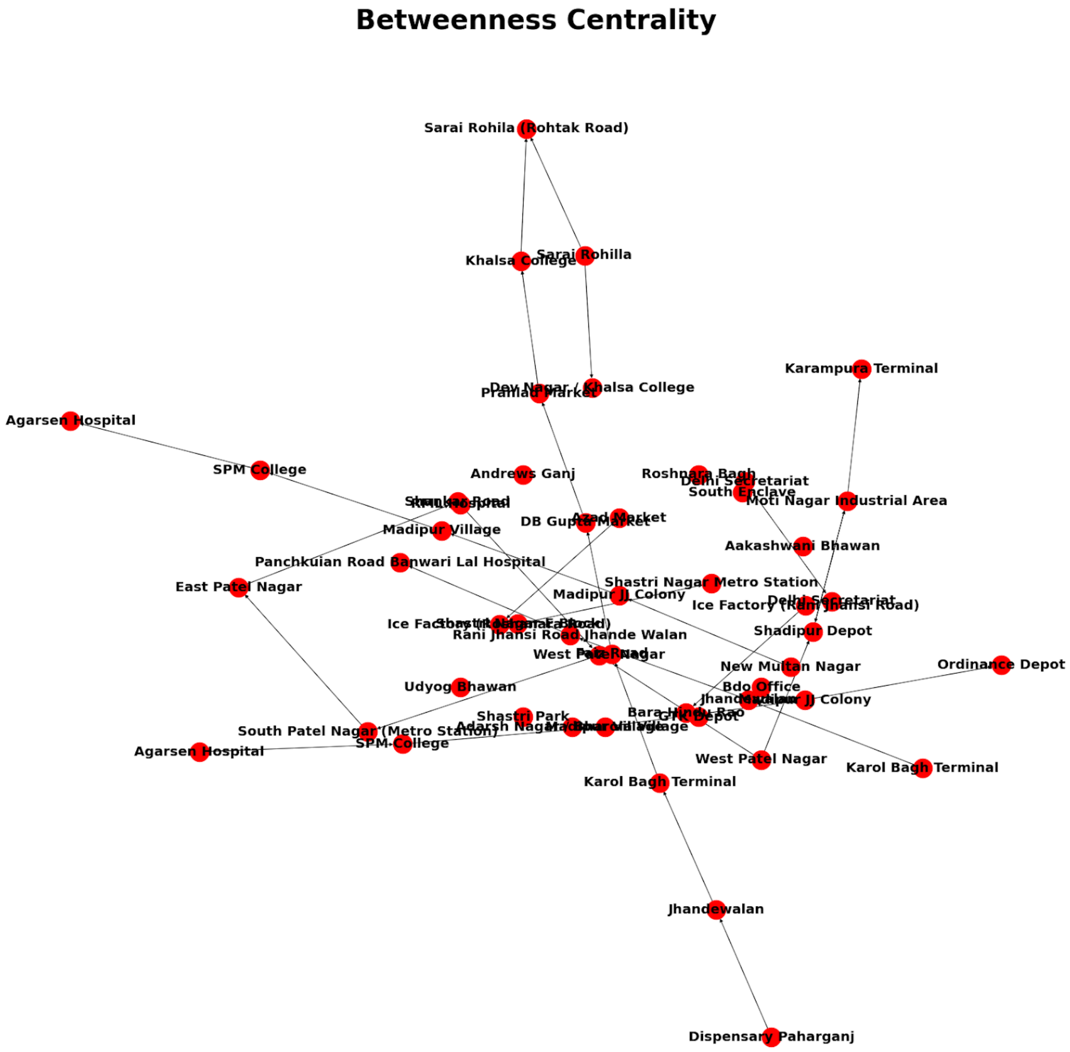


fig 4.2.4(b)

Figure 4.2.4(b) illustrates the top 50 nodes with high betweenness centrality. To compute this, we first calculate edge weights based on latitude and longitude coordinates using the Haversian formula from the geodesic library, yielding distances in kilometers. These distance values are then assigned to the edges' distance attribute, serving as edge weights in our graph. Utilizing the 'betweenness_centrality' function in the 'networkx' library, we identify nodes with high betweenness centrality. The function employs the Brandes algorithm to calculate all shortest paths for each pair of nodes.

4.2 IMPACT OF DISRUPTION SCENARIOS

- ### 4.2.1 Road Closure

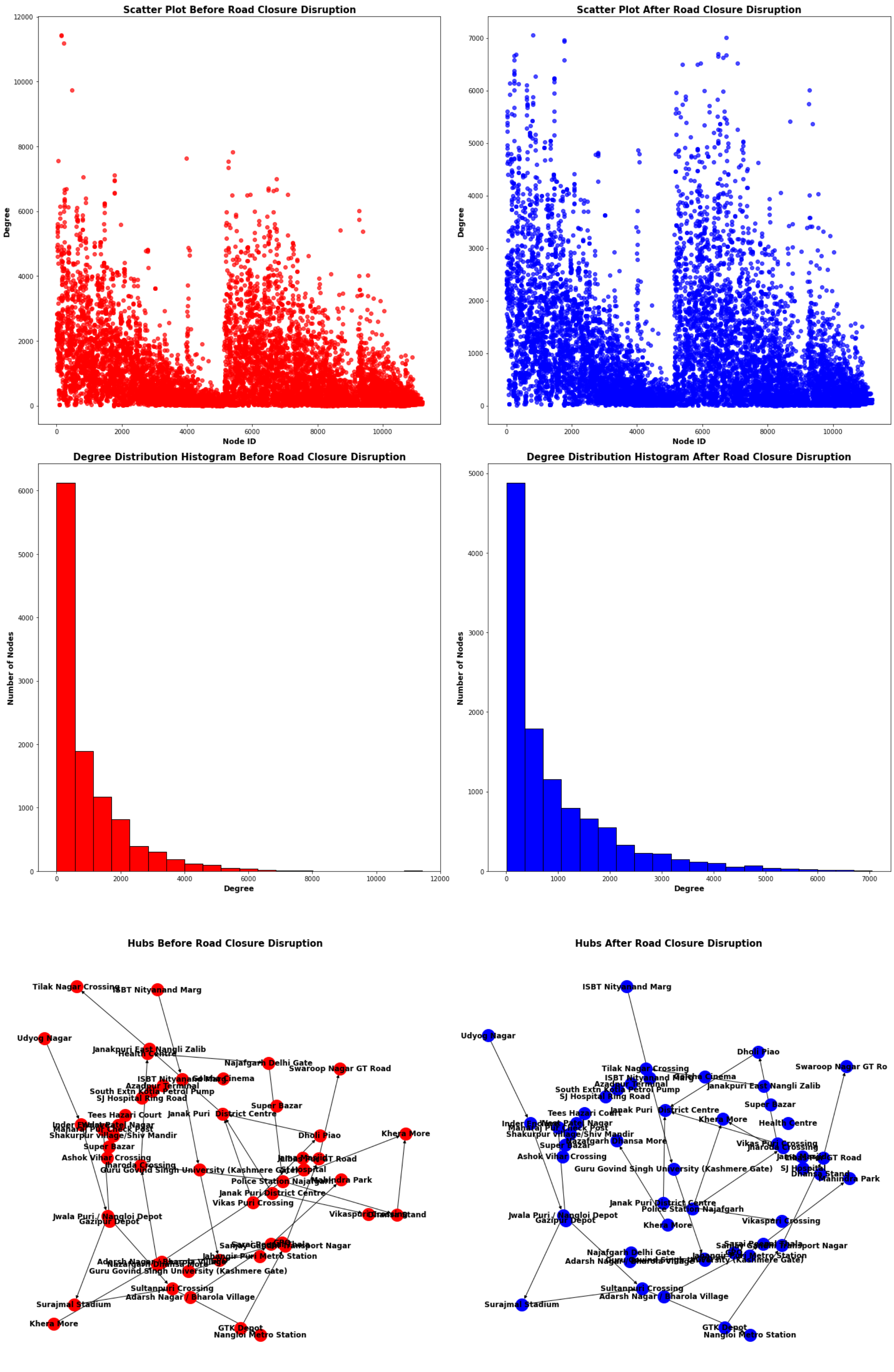


fig 4.2.1 (a)

- ## 4.2.2 Malignant Accidents

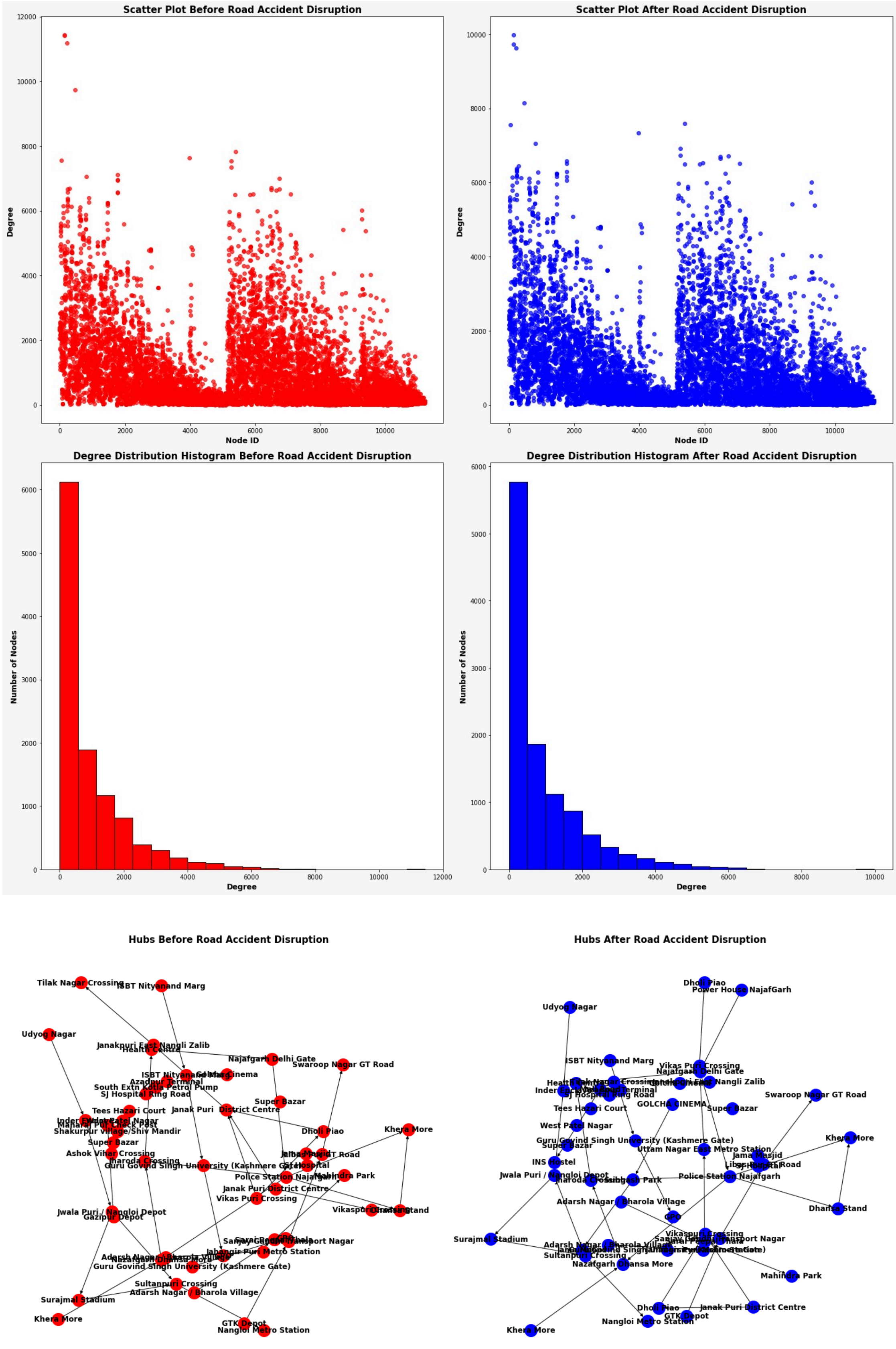


fig 4.2.2 (a)

• **4.2.3 Natural Disasters**

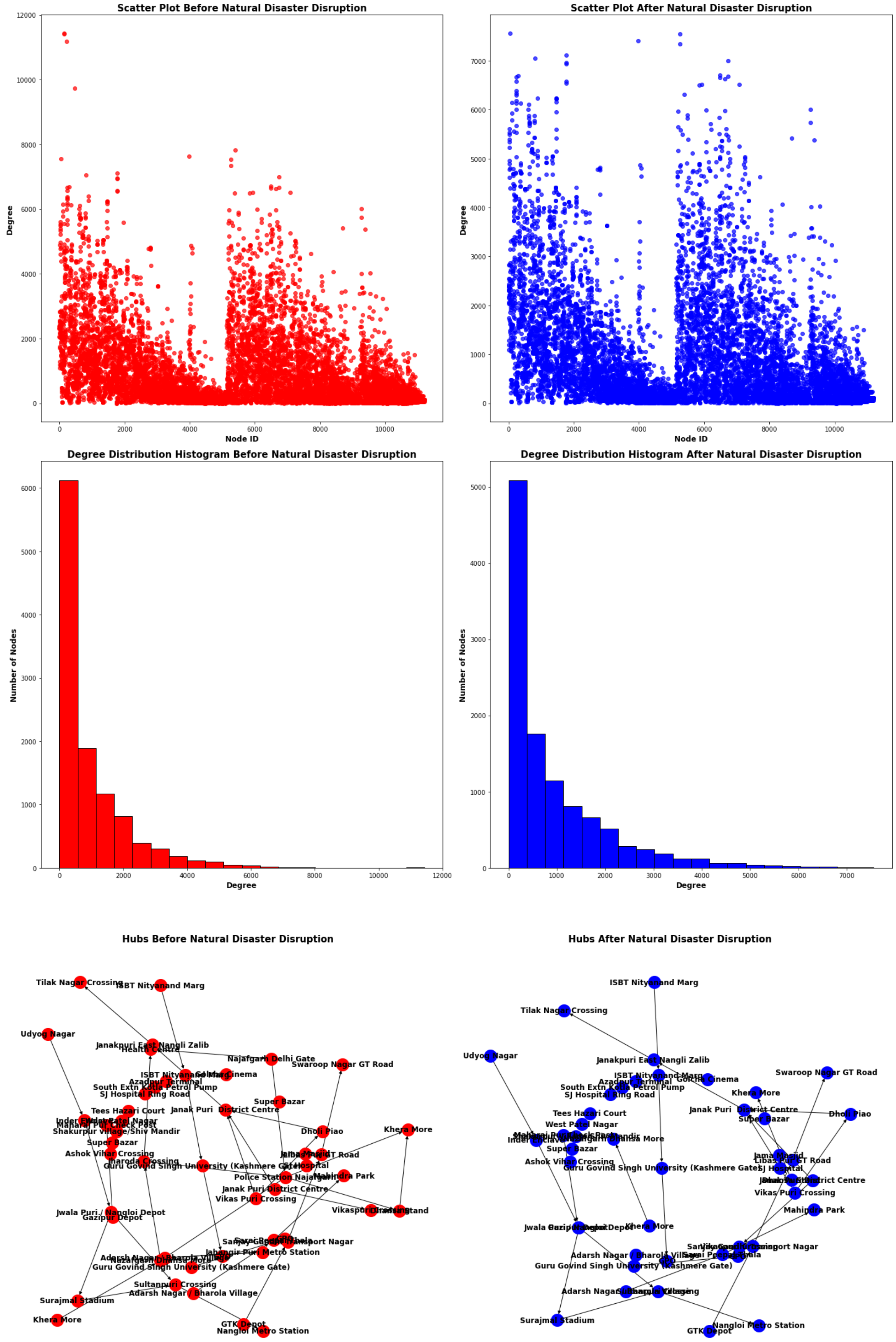


fig 4.2.3 (a)

The figures 4.2.1(a), 4.2.2(a), and 4.2.3(a) illustrate scenarios involving road closures, road accidents, and natural disasters. The red plots simulate road closures, with red graphs depicting conditions before disruptions and blue graphs representing after disruptions.

Disruptions were intentionally introduced to the top 50 hubs in various ways. For road closures, we removed certain edges associated with hubs to observe variations. In the case of road accidents, we removed some trips linked to the hubs, resulting in relatively minor variations. For natural disasters like floods, we simulated disruptions by removing stops and routes associated with those stops, rendering the hubs inaccessible.

While the visual differences are intuitive, it's crucial to note that these simulations, while illustrative, do not provide substantial information for assessing the resilience of the road network. Further analysis and evaluation are necessary to draw meaningful conclusions about the network's ability to withstand and recover from disruptions.

4.3 ROAD NETWORK ROBUSTNESS

- **4.3.1 Function to Calculate Robustness**

```
In [68]: import networkx as nx
         import numpy as np

         # Function to calculate and print degree-based robustness metrics
         def calculate_degree_robustness_metrics(graph, name):
             print(f"\nDegree-Based Robustness Metrics for {name}:\n")

             # Degree sequence of the graph
             degree_sequence = [graph.degree(node) for node in graph.nodes]

             # Average degree
             avg_degree = np.mean(degree_sequence)
             print(f"Average Degree: {avg_degree:.5f}")

             # Standard deviation of degree
             degree_std_dev = np.std(degree_sequence)
             print(f"Standard Deviation of Degree: {degree_std_dev:.5f}")
```

This code calculates and prints two degree-based robustness metrics for a given graph using the NetworkX library. It extracts the degree sequence of the nodes, then computes and prints the average degree and standard deviation of degree for the given graph using numpy. These metrics are fundamental in assessing the robustness and structure of networks in various domains, such as transportation systems or social networks.

- **4.3.2 Road Closure**

```
In [79]: # Calculate and print degree-based robustness metrics for the original graph (G)
         calculate_degree_robustness_metrics(G, "Original Graph (G)")

         # Calculate and print degree-based robustness metrics for Road closures (G_rc)
         calculate_degree_robustness_metrics(G_rc, "Modified Graph after Road Closures (G_rc)")

         Degree-Based Robustness Metrics for Original Graph (G):

         Average Degree: 4.11941
         Standard Deviation of Degree: 2.68405

         Degree-Based Robustness Metrics for Modified Graph after Road Closures (G_rc):

         Average Degree: 4.11406
         Standard Deviation of Degree: 2.67282
```

- **4.3.3 Malignant Accidents**

```
In [76]: # Calculate and print degree-based robustness metrics for the original graph (G)
         calculate_degree_robustness_metrics(G, "Original Graph (G)")

         # Calculate and print degree-based robustness metrics for Malignant Accidents (G_ma)
         calculate_degree_robustness_metrics(G_ma, "Modified Graph after Malignant Accidents (G_ma)")

         Degree-Based Robustness Metrics for Original Graph (G):

         Average Degree: 4.11941
         Standard Deviation of Degree: 2.68405

         Degree-Based Robustness Metrics for Modified Graph after Malignant Accidents (G_ma):

         Average Degree: 4.10651
         Standard Deviation of Degree: 2.12648
```

- **4.3.4 Natural Disasters**

```
In [80]: # Calculate and print degree-based robustness metrics for the original graph (G)
         calculate_degree_robustness_metrics(G, "Original Graph (G)")

         # Calculate and print degree-based robustness metrics for Natural Disasters (G_nd)
         calculate_degree_robustness_metrics(G_nd, "Modified Graph after Natural Disasters (G_nd)")

         Degree-Based Robustness Metrics for Original Graph (G):

         Average Degree: 4.11941
         Standard Deviation of Degree: 2.68405

         Degree-Based Robustness Metrics for Modified Graph after Natural Disasters (G_nd):

         Average Degree: 4.10982
         Standard Deviation of Degree: 2.66600
```

4.4 RECOVERY POST DISRUPTIONS

In this section we implement a rerouting algorithm as a recovery strategy for road network resilience. Here's a simple overview. First we identify the top 20 nodes with the highest degrees in both the original road network (G) and the disrupted network after road closures (G_rc). These nodes are crucial as they have a significant impact on the overall connectivity of the networks.

Then we have used the Kamada-Kawai layout algorithm to define positions for the nodes in both the original and disrupted networks. This layout aims to optimize the spatial arrangement of nodes, enhancing visual clarity.

The function ‘find_shortest_path’ uses the NetworkX library to find the shortest path between two nodes in a given graph. It considers the weighted distance between nodes, providing the most efficient route based on the road network structure.

We apply the rerouting algorithm by finding the shortest paths between the top nodes in the original and disrupted networks. Specifically, it calculates the shortest paths from the highest-degree nodes in the original network to those in the disrupted network.

Next we visualize the road network after the road closure disruption. It also displays the shortest paths between selected nodes in both networks, showcasing the rerouting strategy implemented to recover from disruptions.

The ‘nx.shortest_path’ function is a key component responsible for determining the most efficient path between two nodes in a graph. It utilizes Dijkstra's algorithm by default, considering the weighted distance between nodes for road networks. This function plays a central role in the rerouting algorithm, aiding in the identification of alternative paths for recovery in the disrupted network.

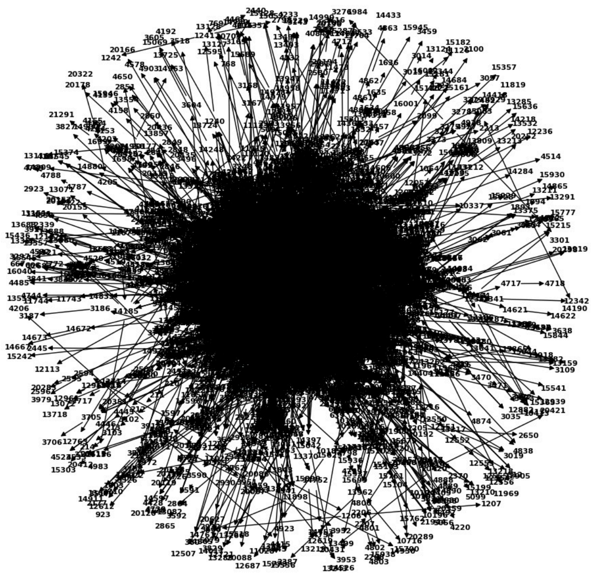


fig 4.3.4 Delhi Road Network After the Application of Re-Routing Algorithm

CHAPTER 5
CONCLUSIONS

5.1 Summary of Key Findings

Our analysis has revealed insightful findings regarding the resilience of the urban road network. The degree distribution analysis indicates a power-law distribution with an alpha value of 3.08, highlighting the scale-free property of the road network. This characteristic suggests that a few highly connected nodes play a crucial role in maintaining overall network connectivity.

In assessing disruption scenarios, we simulated road closures, malignant accidents, and natural disasters. The average degree values for these scenarios are 4.11406, 4.10651, and 4.10982 along with their corresponding standard deviations 2.67282, 2.12648, and 2.66600 provide a measure of the impact on network connectivity. These metrics serve as key indicators of the network's robustness in the face of various disruptions.

5.2 Conclusion

In conclusion, our study demonstrates the inherent resilience of the Delhi Road network, as evidenced by its scale-free property. The analysis of disruption scenarios, including the simulated road closures and accidents, offers valuable insights into the network's response to adverse events. The obtained average degree and standard deviation metrics provide a quantitative understanding of the network's robustness in each scenario.

Moving forward, our findings underscore the importance of devising effective recovery strategies, particularly in the context of rerouting. Leveraging Dijkstra's algorithm for the internal shortest path calculations, we can optimize rerouting options to enhance the network's adaptive capacity. The average degree of 4.11941 and standard degree deviation of 4.10982 for the graph post-disruptions serve as benchmarks for assessing the effectiveness of these rerouting strategies.

As we navigate the dynamic landscape of urban planning, incorporating these insights into the decision-making process will be crucial. The suggested changes to be made based on the rerouting algorithm involve optimizing the road network to align with the observed changes in the graph structure. This iterative process ensures the continuous improvement of urban road infrastructure, fostering a more resilient and adaptive transportation system for the evolving needs of our communities.

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2. Newman, M. E. J. (2018). “Networks: An Introduction.” Oxford University Press. ISBN: 978-0198805090.

Online Resources

1. GitHub Repository - Road Network Robustness:

- Author: Tamene Bekele

- Title: “Road-Network-Robustness”

- Repository URL: [https://github.com/tamene21/Road-Network-Robustness]

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1. Gupta, R. “Evaluation of Accident Black Spots on Roads Using Geographical Information Systems.”

- Author: Rajiv Gupta

- Affiliation: Birla Institute of Technology and Science Pilani

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