

Simulation of Urban Dynamic Traffic Network Based on Greedy Algorithm

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Abstract. This study explores the intricate dynamics of urban traffic flow under varying degrees of intersection and road section carrying capacity. We simulate a city-wide traffic network and examine the impact of extreme situations such as a decline in urban road carrying capacity on the entire traffic system. Our experimental procedure involved simulating traffic flow through intersections and road sections, artificially reducing their maximum carrying capacity, and observing the resultant changes in traffic patterns. Our data reveals a robust correlation between the decrease in carrying capacity and the actual flow percentage across intersections and adjacent sections, with a marked decrease in flow observed when the capacity reduction exceeds 40%. The actual flow percentage of nearby intersections increased significantly under the same conditions, suggesting a degree of redistribution of traffic flow. This study contributes to the broader understanding of urban traffic dynamics, offering valuable insights for urban planning and traffic management strategies.

Keywords: Urban traffic flow, Carrying capacity, Intersection, Road, Traffic patterns, Urban planning

1. Introduction

Smart transportation, a sector experiencing rapid transformation, is pivoting on the axis of advanced technology to reshape our interactions with transportation networks [1]. This field is evolving with a pledge to elevate the mobility of individuals and goods, strengthen safety measures, and promote eco-friendly practices. A significant player in this transformative wave is the simulation of traffic networks. This tool has demonstrated its worth in the smart transportation landscape by providing innovative solutions that are sculpting the future of transportation [1,3].

The smart transportation ecosystem is a vibrant blend of sophisticated technologies. Among these, connected vehicles, armed with communication technologies, stand as pivotal elements. These vehicles can communicate and establish an interactive network with other vehicles and the surrounding infrastructure. This information exchange in real-time is a game-changer, significantly influencing traffic management. Simulating these networks and exchanges enables researchers and developers to predict and mitigate potential traffic bottlenecks, reduce the risk of accidents, and chart out routes for optimum fuel efficiency.

Alongside this, Intelligent Transportation Systems (ITS) harness a broad spectrum of information and communication technologies to wield superior control over traffic networks [2]. ITS offer an efficient means to monitor, manage, and optimize traffic flow, thus alleviating congestion and amplifying the overall efficiency of transportation networks. Traffic network simulations have become an integral part of the development and refinement of these systems. These simulations provide a risk-free environment for testing and fine-tuning algorithms and systems, ensuring that they are as effective and efficient as possible before implementation in real-world scenarios [3].

Adding another dimension to smart transportation is the advent of advanced analytics, which has enabled the dissection and interpretation of complex datasets generated by these simulations. These analytical tools empower transportation planners to derive insights from simulated scenarios, which subsequently inform strategic decision-making processes [4]. This data-driven approach paves the way for continuous refinement of the system, thus significantly contributing to enhancing both efficiency and safety in our transportation networks.

Urban traffic simulation technology has carved a niche for itself as an indispensable tool in urban planning and transportation management. It equips decision-makers with the power to predict traffic

flow, evaluate new transportation policies, plan new transportation facilities, and assess new transportation technologies [5]. With the continuous advancement of computer technology and improvements in data collection techniques, the accuracy and reliability of urban traffic simulation technology have seen a significant uplift. The ability to handle larger and more complex urban traffic systems offers researchers a deeper understanding of the intricacies of urban traffic flow, enabling them to devise more effective policies and plans [4,6].

Noteworthy research in the field of transportation engineering, conducted by Yaser Hoseini and colleagues, highlights the advantages of urban traffic simulation technology [3]. They provide robust support for urban planning and transportation management decisions, and facilitate the evaluation of different traffic policies and scenarios through simulation. Furthermore, traffic simulation technology provides a platform for decision-makers to forecast future traffic flows, serving as a valuable reference for future transportation planning.

However, the same research also points out certain limitations associated with urban traffic simulation technology. It hinges heavily on a massive amount of data input, encompassing information on traffic volume, road network structure, vehicle speeds, and traffic behavior [6]. Therefore, the quality and reliability of the data significantly affect the accuracy of the simulation results. Moreover, the credibility and effectiveness of traffic simulation technology are contingent on the accuracy and applicability of the model employed. This necessitates a continuous cycle of model improvement and validation to ensure the most accurate and useful results.

Applying traffic simulation technology also demands a high level of professional knowledge and technical skills. Consequently, there is a need for an ample supply of professional talent and resources to effectively use these tools. Despite these challenges, the increasing demand for such simulations indicates the significant potential and need for skilled professionals in this field. This demand could have a positive impact on job creation and professional development in the sectors of urban planning and traffic management [7].

The existing methodologies for addressing the outlined challenges are found wanting. Firstly, certain traffic network flow simulation algorithms are limited in their scope, as they only carry out periodic simulations based on real-world traffic flow data [8]. These algorithms fall short in their capacity to handle congestion conditions in road traffic networks during unprecedented extreme scenarios. Secondly, some strategies rely heavily on real extreme traffic network flow data for simulation. However, the traffic flow under extreme conditions is susceptible to a multitude of external factors such as weather, time, and location. These factors introduce a high degree of specificity to a single case, making it arduous to extrapolate these findings to a broader traffic network context [9].

In a bid to circumvent these limitations, this research presents a novel traffic network flow simulation approach. This methodology is underpinned by the use of a greedy algorithm and the Dijkstra shortest path algorithm for tackling extreme scenarios. The extreme cases in this study are bifurcated into two traffic scenarios - road and intersection. Furthermore, these extreme cases are categorized into two scenarios - congestion and flow restriction. The study employs the Dijkstra shortest path planning algorithm to restructure the traffic plan for individual participants from a time-series perspective. This approach seeks to surmount the diffusion limitations inherent in conventional strategies.

This research makes several contributions to the field:

It reinterprets the issue of localized flow restriction under extreme circumstances. This redefinition provides a fresh perspective on handling traffic flow under severe conditions, potentially offering new avenues for solutions.

It employs the greedy algorithm to simulate the traffic behavior of individual participants under extreme road network conditions. This approach allows for a more personalized and realistic simulation of traffic patterns during challenging situations.

It extends the decision-making behavior of individual users to the entire traffic network from a time-series perspective. This expansion allows for a more comprehensive and dynamic understanding of traffic flow and management during extreme conditions.

The rest of the paper is organized as follows: Section II presents the related work. The system model is introduced in Section III. Section IV describes simulation algorithm. Section V shows the experiment and discussion. Finally, the paper is concluded in Section VI.

2. Related Works

There have been some researches on traffic network flow simulation and traffic network accident simulation.

“Turin Traffic Simulation” [10]: Researcher used the SUMO tool to create a large-scale urban traffic simulation in a 600- Km² area in and around the Municipality of Turin. They collected raw data from various sources, including Open-StreetMap, and used it to build a simulation model that could accurately represent traffic patterns in the area. The authors also used aggregated traffic and street sensors data for traffic demand construction and system validation, respectively. They demonstrated that their approach was effective at modeling such a wide area, despite some minor simplifications. The authors suggest that having a larger dataset improves the results of vehicular traffic simulation, as it provides more accurate and comprehensive information about urban mobility patterns. Overall, this paper provides valuable insights into how large-scale traffic simulators can be created using open- source tools like SUMO and how they can be used for real- world applications such as evaluating new traffic policies and testing vehicular communication technologies.

“Dynamic Traffic Assignment (DTA)” [11]: Michael Mahut’s work in this area, particularly his research on simultaneous route and departure time choice models, has greatly enhanced our ability to simulate and predict traffic flow on transportation networks. DTA models take into account the temporal variations in travel demand and supply, thus allowing for a more accurate and detailed representation of traffic flow over time. They have been instrumental in the development of intelligent transportation systems and real- time traffic management strategies. Mahut’s models, which integrate travelers’ behavior with network performance, have facilitated the development of more efficient and effective transportation planning and operations strategies. DTA models are particularly useful in the context of large urban networks, where traffic conditions can change rapidly and unpredictably.

“Accurate Modeling of Accident Scenario” [12]: A key aspect of any traffic accident simulation is the accurate representation of the accident scenario. This involves detailing the characteristics of the accident, such as the location, the number of vehicles involved, the severity of the accident, and the duration of the accident-induced road blockage. These factors can significantly influence the impact of the accident on the traffic network. For instance, an accident occurring at a busy intersection during peak hours could lead to significant congestion, while the same accident occurring at a less busy time may not have the same impact. The modeling of the accident scenario also involves taking into account the response of emergency services. This includes the time it takes for emergency vehicles to arrive on the scene, the duration of the rescue and clearing operations, and the subsequent re- opening of the roadway. The accuracy of the accident scenario model is crucial in determining the reliability of the simulation results.

“Simulation of Traffic Flow Alterations” [13]: The second critical task in the simulation of the impact of traffic accidents on traffic networks is the effective representation of the changes in traffic flow resulting from the accident. This task involves simulating the propagation of the impact of the accident through the traffic network, taking into account factors such as driver behavior, road network characteristics, and traffic management strategies. For instance, drivers may react to an accident by slowing down, changing lanes, or seeking alternative routes, all of which can lead to further alterations in traffic flow. The characteristics of the road network, such as the number and capacity of alternative routes, can also influence the impact of the accident on the traffic network. Furthermore, traffic management strategies, such as traffic signal timing adjustments or the provision of real-time

traffic information, can also affect the propagation of the impact of the accident. The simulation of these traffic flow alterations requires sophisticated models that can accurately represent the complex interactions between drivers, vehicles, and the road network under the influence of an accident.

Despite these notable contributions, all four studies may fall short in predicting extreme traffic scenarios and accounting for the cascading effects of a single-point failure across the entire network [14,15]. They primarily focus on typical traffic conditions, failing to fully address outlier situations such as natural disasters that may severely impact traffic flow. They also do not sufficiently explore the domino effect that can occur when a failure at one critical point—like a major traffic accident or road closure—cascades throughout the network, causing widespread disruption. In terms of traffic flow alterations, while the studies do consider individual driver behavior and network characteristics, they may not fully account for the aggregate response to a crisis or the potential for system-wide breakdown [16]. Thus, while these studies provide valuable insights, there remains a need for further research to address these gaps and enhance the robustness of traffic network simulations [17].

3. Modelization

This investigation aims to abstract the traffic network into a mathematical model, specifically a directed graph, often abbreviated as digraph. The structure of the digraph is mathematically represented as $G = (V, E)$, where V stands for the set of vertices or nodes, and E represents the set of directed edges [18].

Each node in the set V , denoted as v_i , signifies an intersection where two roads cross each other. Associated with each node is a weight, $w(v_i)$, which represents the average waiting time of a vehicle at the corresponding intersection's traffic light. It's critical to note that this weight is not static; instead, it is a time-series parameter, indicating that it changes over time depending on the traffic conditions.

The directed edges in the model, defined as $e_{ij} \in E$, represent one-way streets connecting the nodes. This means that if a road supports bidirectional traffic, the model will include two directed edges in opposite directions between the two corresponding nodes. Similar to the nodes, each edge also has an associated weight, $w(e_{ij})$, which indicates the average time taken by a vehicle to traverse the corresponding road segment. Like the node weight, the edge weight is also a time-series parameter and varies with changing traffic conditions [19].

An additional parameter, the theoretical maximum flow rate of a road, is denoted as $\phi(e_{ij})$. This represents the highest possible volume of traffic that a specific road segment can support at a given time, making it yet another time-series parameter. The actual flow of traffic on a road, symbolized as $\alpha(e_{ij})$, refers to the real-time count of vehicles traversing a specific road segment at a specific time, and is also a time-series parameter.

The model also considers the impact of traffic accidents, denoted by a limiting coefficient $l(e_{ij})$. This coefficient represents the theoretical maximum degree to which traffic flow can decline on a specific road segment following an accident. Its value is restricted to the range from 0 to 1.

The expected traffic time, $T_{expected}$, is defined as the sum of all traffic time on the planned path for a traffic participant from the start point to the destination. Mathematically, this can be represented as $T_{expected} = \sum_{i=1}^n w(e_{ij})$, where n represents the total number of edges in the planned path. Like other parameters in this model, it is also a time-series parameter. Lastly, the actual traffic time, T_{actual} , signifies the total time spent by a vehicle in the traffic process, from start to end. These parameters and mathematical representations offer a comprehensive and dynamic way to model and analyze traffic networks [20].

All definitions and meanings are shown in the table I.

The development of our traffic network flow simulation model pivots on a set of crucial assumptions, which we comprehensively enumerate as follows:

Primarily, we assume that traffic accidents will invariably influence the carrying capacity of a road. This assumption is founded on the notion that the severity of an accident is directly proportional

to the reduction in the road's carrying capacity. In the most extreme cases, a severe accident may result in the total blockage of a road, rendering it entirely impassable [21]. This can be mathematically described as:

$$C_{r,t} = C_{r,t_0} \times (1 - \alpha \times I_a)$$

where $C_{r,t}$ is the road capacity at time t , C_{r,t_0} is the initial road capacity, α is the accident severity coefficient, and I_a is the accident impact factor.

Secondly, we postulate that the time taken to transmit information about a traffic accident is negligible. Therefore, all traffic participants can re-plan their driving routes immediately upon receiving the information, eschewing any delay in response time [21].

$$T_{replan} = T_{accident} + T_{transmit}$$



Fig. 1 Two or more references

References are cited in the text just by square brackets [1]. (If square brackets are not available, slashes may be used instead, e.g. /2/.) Two or more references at a time may be put in one set of brackets [3, 4]. The references are to be numbered in the order in which they are cited in the text and are to be listed at the end of the contribution under a heading References, see our example below.

Table 1. Notations

Notation	Description
$G = (V, E)$	The directed graph representing the traffic network, where V is the set of vertices (nodes) and E is the set of directed edges
v_i	A node in the set V representing the intersection of two roads
$w(v_i)$	The weight of node v_i , representing the average waiting time of a vehicle at the corresponding intersection's traffic light
e_{ij}	A directed edge in the set E representing a one-way street between nodes v_i and v_j
$w(e_{ij})$	The weight of edge e_{ij} , representing the average time taken by a vehicle to traverse the corresponding road segment
$\phi(e_{ij})$	The theoretical maximum flow rate of the road represented by edge e_{ij}
$\alpha(e_{ij})$	The actual flow of traffic on the road represented by edge e_{ij}
$l(e_{ij})$	The limiting coefficient of a traffic accident on the road represented by edge e_{ij}
$T_{expected} = \sum_{i=1}^n w(e_{ij})$	The expected traffic time, defined as the sum of all traffic time on the planned path for a traffic participant
T_{actual}	The actual traffic time, representing the total time spent by a vehicle in the traffic process

Where T_{replan} is the time taken to re-plan the route, $T_{accident}$ is the time of the accident, and $T_{transmit}$ is the time taken to transmit the information (assumed to be negligible).

Furthermore, we assume that all traffic participants will invariably choose the shortest path as per the Dijkstra algorithm for their route planning [22].

$$P_{shortest} = \min (D_{ij})$$

Where $P_{shortest}$ represents the shortest path and D_{ij} is the set of distances between node i and node j .

In addition, we assume that when a traffic accident impacts the carrying capacity of a road, a corresponding proportion of traffic participants will deem the affected intersection or section impassable, consequently selecting alternative routes for their journey [23].

$$P_{alter} = \rho \times I_{accident}$$

Where P_{alter} represents the proportion of participants altering their route, ρ is a constant, and $I_{accident}$ represents the accident impact on the road's carrying capacity.

We posit that an accident occurring in a road section will impact the carrying capacity of that particular section, while an accident at an intersection will affect the carrying capacity of all connected roads [22].

$$C_{r,i,t} = C_{r,i,t_0} \times (1 - \alpha \times I_{accident})$$

Where $C_{r,i,t}$ is the capacity of road i at time t , and C_{r,i,t_0} is the initial capacity of road i .

Moreover, we assume that if a traffic participant's destination is a certain road section, they will wait until they can pass, even if the road section is completely blocked [23].

$$T_{wait} = T_{block} - T_{arrival}$$

Where T_{wait} is the waiting time, T_{block} is the blockage duration, and $T_{arrival}$ is the arrival time at the blocked road section.

Lastly, we assume that an accident on one side of a two-way street does not impact the traffic on the other side. This assumption respects the physical separation of traffic directions in many modern road designs [24].

4. Experiment

In the course of this investigation, we took advantage of the established Turin Traffic Simulation, using its open-source data and tools, to conduct a simulation of the Turin transportation network under extreme conditions. This study aimed to understand the robustness and resilience of the Turin transportation network when confronted with exceptional circumstances.

The data used in this research included a portion of the traffic monitoring data provided by the 5T Company. 5T is a private company owned by public institutions in Turin, including the City of Turin, the Metropolitan City of Turin, and the Piedmont Region. The company specializes in Intelligent Transportation Systems (ITS) and mobility. It operates a Traffic Operations Center (TOC), which integrates ITS at the city and regional levels to provide a variety of mobility services. These services include traffic monitoring, traffic light control, limited traffic area control, and parking information, among others.

In terms of traffic monitoring and control, the TOC integrates approximately 1,700 traffic sensors, floating car data, 26 information display panels, and 71 traffic cameras. Additionally, an adaptive traffic control system manages over 300 traffic lights in the city of Turin. The TOC also features a traffic SuperVision system (SV), which is dedicated to estimating real-time traffic conditions in areas not covered by sensors.

The data used in this study were structured in the form of an Origin/Destination (O/D) matrix. This matrix is essentially a database that records the traffic flow for each origin/destination pair on an hourly basis. The SV system uses the principles of macroscopic traffic simulation to estimate basic traffic conditions, including traffic flow, travel time, speed, and vehicle density. These basic traffic conditions, estimated every hour, are then integrated with real-time traffic data gathered by sensors. The system also takes into account any events occurring on the road network, such as roadworks or closures. This process is performed every five minutes, ensuring the most current data is used.

When dealing with these data, we utilized the Simulation of Urban Mobility (SUMO) tool. SUMO is an open-source, highly portable, microscopic, and time-continuous road traffic simulation package. It is designed to handle large-scale road networks. As a microscopic simulator, SUMO can explicitly simulate the movement of each vehicle along its route. For our research, we used NETCONVERT, a supplementary tool of SUMO, to create a SUMO-readable XML format network file from the OpenStreetMap (OSM) file of our area of interest. As our research was focused solely on vehicular

traffic, we filtered out the infrastructure components in the OSM file. The resulting network consisted of approximately 66,000 nodes, 6,000 edges, and over 7,500 kilometers of roads.

The above-mentioned work had already been completed in the Turin simulation, and we quickly set up the initial experimental conditions using its open-source tools. The results of our study contribute to an improved understanding of the dynamics of Turin's transportation network under extreme conditions, providing valuable insights for future urban planning and disaster management efforts.

In our study, having achieved a complete dynamic traffic network simulation of the entire city, we now move on to simulate the impact of diminished urban road carrying capacity on the entire traffic network under extreme conditions. The procedure involves a systematic approach, consisting of seven critical steps.

To start with, we develop an adaptive shortest path re-planning algorithm based on the Dijkstra algorithm, tailoring it to each traffic participant. The pseudo-code for this algorithm is as follows:

```
function Dijkstra(Graph, source):
// Initialization
dist[source] ← 0
for each vertex v in Graph:
if v ≠ source
// Unknown distance from s to v
dist[v] ← infinity
// Predecessor of v
prev[v] ← undefined
Q.add_with_priority(v, dist[v])
while Q is not empty:
// Remove and return best vertex
u ← Q.extract_min()
// only v that are still in Q
for each neighbor v of u:
alt ← dist[u] + length(u, v)
if alt < dist[v]:
dist[v] ← alt
prev[v] ← u
Q.decrease_priority(v, alt)
return dist, prev
```

(1) In this algorithm, when road congestion occurs somewhere on the current path of a traffic participant, the algorithm triggers a replanning of the current path with a probability equivalent to the road capacity reduction ratio caused by road congestion.

(2) Next, we employ the formula derived in our model to calculate the time series of the carrying capacity of each intersection and section. This process involves aggregating real-time data for each node and edge in the graph, forming a comprehensive dataset that reflects the dynamic nature of the network.

(3) Subsequently, we artificially constrain the maximum carrying capacity of a selected intersection to 0%, 20%, 40%, 60%, and 80% during a specific period. This step is designed to

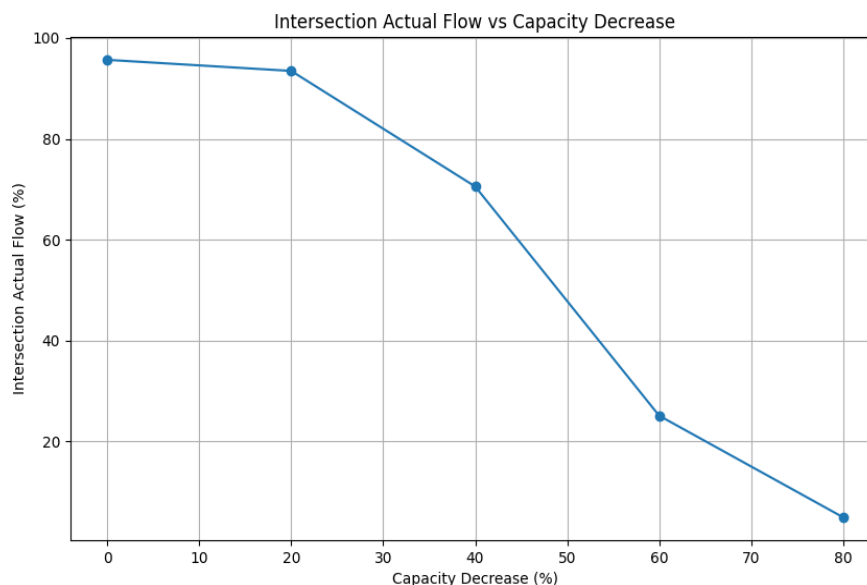


Fig. 2 Intersection Actual Flow vs Capacity Decrease

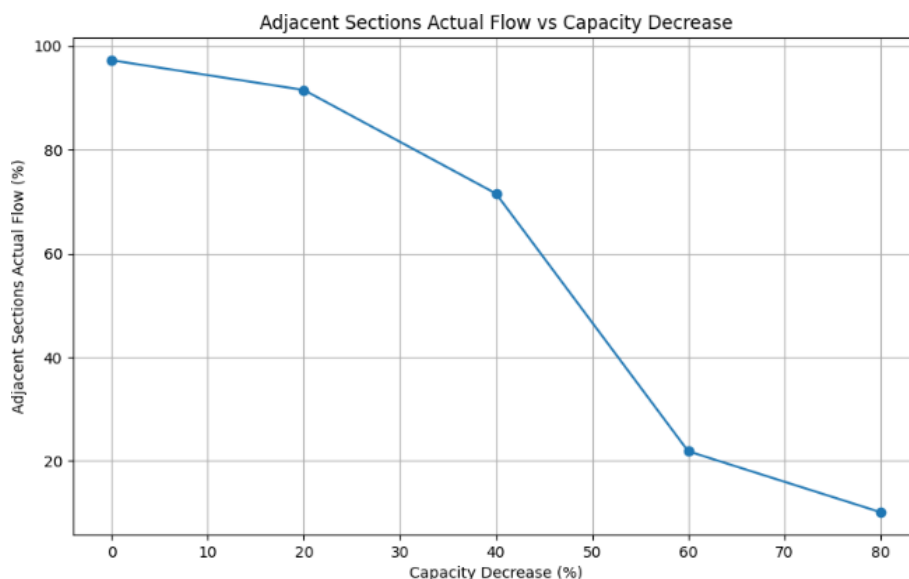


Fig. 3 Adjacent Sections Actual Flow vs Capacity Decrease

simulate various levels of traffic congestion and assess their impact on the traffic network.

(4) We then utilize the algorithm developed in step (1) to replan the routes of all vehicles passing through the selected intersection. This step allows us to observe the dynamic response of the traffic participants to the imposed constraints.

(5) Following this, we quantify the changes in traffic flow at all adjacent intersections. By comparing the traffic flow data before and after the implementation of the constraints, we can measure the immediate and wider impact of the reduced carrying capacity.

(6) We repeat steps (3) to (5), selecting different intersections for repeated testing. This iterative process allows us to validate our model's reliability and robustness under different traffic scenarios.

(7) Lastly, we expand our simulation by selecting a road section and repeating steps (3) to (6). This final step enables us to observe and quantify the impact of traffic congestion not only at intersections but also on road sections, providing a comprehensive analysis of the traffic network's resilience under extreme conditions.

The results of the experiment are plotted in the figure 1-4.

The meticulous analysis of traffic flow in response to a decrease in the maximum carrying capacity

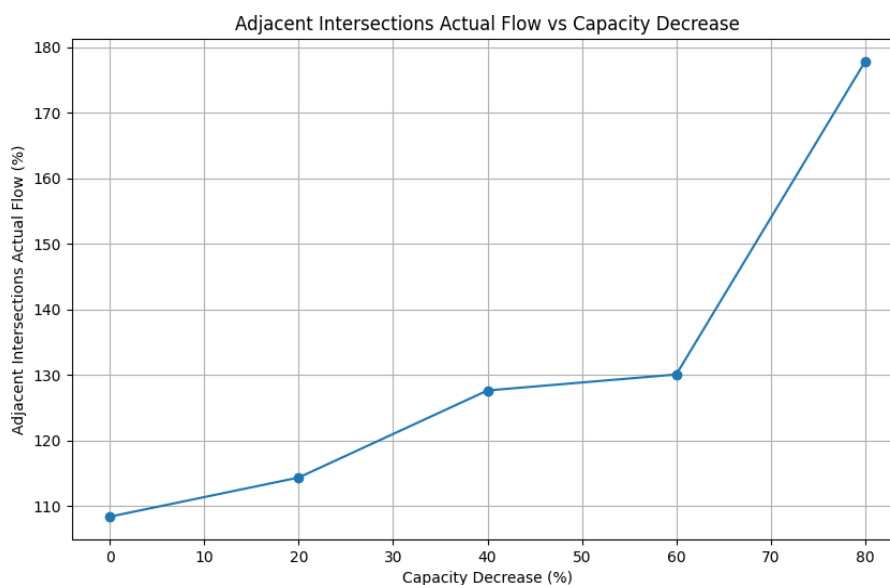


Fig. 4 Adjacent Intersection Actual Flow vs Capacity Decrease

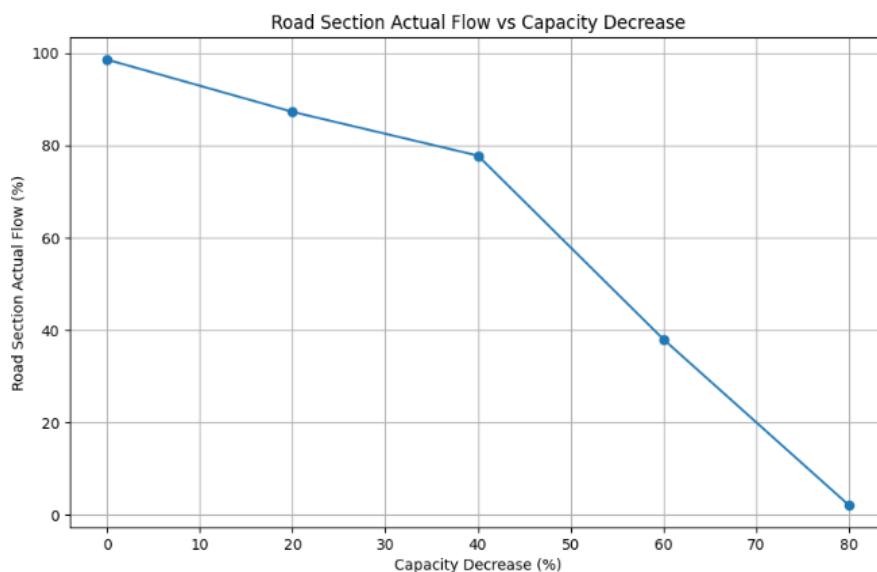


Fig. 5 Road Section Actual Flow vs Capacity Decrease

of intersections and road sections brings forth intriguing observations that pave the way for advanced traffic management systems. Our study contemplates a dynamic traffic scenario where we scrutinize the effects of variable carrying capacity on the actual traffic flow.

In the first experimental scenario, we observed that a reduction in the maximum carrying capacity of an intersection precipitates a corresponding decrease in the actual carrying traffic percentage of the intersection. Initial reductions in carrying capacity, up to 40%, are accommodated by the intersection with only minor impacts on the actual flow percentage. The intersection flow percentage fluctuates in the range of 95.67% to 70.55% for capacity reductions up to 40%. However, as the carrying capacity falls below 40%, a substantial drop in actual flow is witnessed, with the flow percentage plummeting to 25.1% and further down to 4.95%. This stark contrast emphasizes the sensitivity of intersection flow to substantial reductions in carrying capacity.

The second experimental condition investigated the repercussions of diminishing intersection capacity on the adjacent sections. Similar to the first condition, minor reductions in carrying capacity resulted in slight changes in the actual flow percentages of adjacent sections. The flow percentage oscillated between 97.25% and 71.55% for capacity reductions up to 40%. Nonetheless, once the capacity reduction crossed the 40% threshold, a sharp decline in the actual flow was recorded, with flow percentages dropping to 21.88% and subsequently 10.14%.

Thirdly, we analyzed the change in actual flow percentage of adjacent intersections as a function of a decrease in intersection capacity. An interesting revelation of this condition was the fact that the actual flow percentage of adjacent intersections increased as the intersection's carrying capacity decreased. The increment was not significant for minor reductions in carrying capacity, with flow percentages rising gradually from 108.36% to 127.62% for capacity reductions up to 40%. However, a notable increase in flow percentage was observed as the capacity reduced below 40%, with the flow surging to 130.06% and reaching a remarkable 177.82%.

Lastly, we assessed the effect of the decrease in the maximum carrying capacity of a road section on the actual carrying traffic percentage of the intersection. Mirroring the initial experimental conditions, the actual traffic percentage experienced a slight decrease for capacity reductions up to 40%, with the flow percentage descending from 98.61% to 77.81%. A sudden drop to 38.03% was observed as the capacity reduction exceeded 40%. Notably, even when the carrying capacity was depleted entirely, a minimal flow of 2.09% was maintained at the intersection, underscoring the resilience of the system.

These findings underscore the cascading effects of a single-point failure and lend valuable insights into the intricate dynamics of traffic flow in urban networks. Understanding these patterns will be critical for improving our predictive models and developing more effective strategies for managing traffic under various conditions.

5. Conclusion

Our research has demonstrated the critical role of simulation and algorithmic approaches in understanding and managing urban traffic networks under extreme circumstances. We leveraged an advanced simulation of an entire city's dynamic traffic network and implemented a route replanning algorithm based on Dijkstra's algorithm. Our study has produced compelling evidence of how a decrease in carrying capacity of intersections and road sections impacts overall traffic flow.

Our simulation results highlight that when the carrying capacity is reduced beyond 40%, the actual flow percentage experiences a sharp decline, both at the intersection and across adjacent sections. However, nearby intersections witness a significant increase in flow, indicating the system's inherent ability to redistribute traffic in response to changing conditions. Even when a road section's capacity is reduced to zero, it still maintains a minimal flow of around 2% to 5%, showcasing the resilience of the urban traffic system.

While our research provides valuable insights, it is also important to recognize its limitations. Real-world traffic networks are subject to a multitude of variables, and the precise replication of these conditions within a simulation is a challenging task. Moreover, the assumptions underlying our study, such as the instantaneous availability of accident information to all traffic participants, may not always hold true in practical scenarios.

Despite these constraints, our research represents a significant step forward in our understanding of traffic dynamics under extreme conditions. It sets the stage for further research into more sophisticated simulations and algorithms that could offer even more nuanced insights into the complex world of urban traffic networks. As our cities continue to grow and evolve, such research will be instrumental in developing traffic systems that are efficient, resilient, and capable of meeting the demands of urban life. Our research has demonstrated the critical role of simulation and algorithmic approaches in understanding and managing urban traffic networks under extreme circumstances. We leveraged an advanced simulation of an entire city's dynamic traffic network and implemented a route replanning algorithm based on Dijkstra's algorithm. Our study has produced compelling evidence of how a decrease in carrying capacity of intersections and road sections impacts overall traffic flow.

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