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Evaluating the Impact of Bi-directional Traffic Flow on Urban Road Efficiency: A Case Study of Norwalk, CT, USA

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Abstract

Urban road efficiency is one of the most important facets of transport planning that holds huge implications for traffic flow rates, travel times, and overall mobility in urban areas. This study focuses on the influence of bi-directional traffic flow on urban road efficiency and takes Norwalk, CT as a case study. Arising from this, a holistic dataset with different traffic variables, such as average speed, vehicle delays, and free-flow factors was used to analyze the performance of bi-directional zones of the city's road network. From the analysis, bi-directional traffic zones have very varying efficiency levels, with average speeds ranging from 4 mph to 43 mph and very different vehicle delays. The median travel speed for these areas averaged 18 mph, which suggests moderate congestion. The average daily traffic volume was vastly different: some barely had any traffic, while others were as high as over 26,000 vehicles per day. The study also found that some of the variables used, like zone length and traffic volume, played a very important role in determining road efficiency; in most cases, longer zones and higher volumes increased delays and lowered speeds. Comparative and correlation analyses prove that, compared to the non-bi-directional zones, bi-directional zones generally sustain higher vehicle hours of delay. That is, as much as the bi-directional flow would accommodate traffic from both directions, under specific conditions, it contributes to congestion. Therefore, from the results, it follows that target-oriented traffic management strategies is required to optimize road efficiency in bi-directional zones, more so within an urban setup with constraints in space and infrastructure. The study concludes with several major recommendations to urban planners and traffic engineers for the adoption of context-specific solutions to making the road more efficient in bi-directional zones.

Keywords: Bi-Direction; Uni-Direction; Traffic flow; Urban Road; Delays; Congestion; Efficiency

1. Introduction

In evaluating the value and significance of bi-directional traffic flow on urban road efficiency, it is necessary to examine in detail the traffic dynamics, especially in areas where the road space is limited, and traffic volumes are high. This is why using Norwalk, CT, as a case study is crucial due to its diverse traffic patterns and varied road designs. The study aim is to explore the efficiency of bi-directional traffic zones by analyzing key variables such as average speed, vehicle delays, and daily traffic volumes.

From the study, there are considerable disparities in traffic efficiency for bi-directional zones, confirming earlier research, with observed average speeds from 4 miles per hour to 43 miles per hour and meaningful differences in vehicle delay. Certain bi-directional zones experienced volumes at 26,000 vehicles per day with other bi-directional zones processing much lower pre-volume estimations which reflect the varying impact on efficiency on the studied roadways. Research has consistently supported findings denoting the multifaceted considerations of managing bi-

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directional zones, particularly in urban areas with pre-existing limits to roadway capacity. According to Yang *et al.* (2023), the synchronizing of signals at intersections plays a significant role in the management of bi-directional flows, particularly in urban trends in roadway inflection. These observations reinforced the findings early on that longer bi-directional zones with higher volumes of traffic also produced higher delay rates while subsequently producing slower average speeds.

Additionally, the analysis in Norwalk, CT., provides the first framework reported that addresses how roadway design considerations and decision making strategies with implications to bi-directional objectives improve efficiency outcomes within bi-directional zones. For example, Kang *et al.* (2024) suggested that coordination of signalization within and surrounding complex urban networks significantly improves traffic flow in bi-directional zones. This documentation supports the position to advance localized saturation or management considerations while acknowledging the value underlying extreme volume and road layouts for the management utility of bi-directional zones.

The study indicated conceptual reflections of Norwalk, CT's bi-directional experience providing a glimpse into the unique issues and queries faced with bi-directional roadway design in urban settings. This consideration succinctly emphasized sessional-based adaptability or informed prior considerations regarding the importance of characteristics with road layout, or the need for places that devote attention to managing lane distances. Together with route volumetric probable issues that spatially contribute to the overall traffic flow experience, it could be helpful. Considering local context scenarios involving assignments to potential instigators to overall improvements first consider the net benefits would not be lost. These insights draw broader implications to urban planning or traffic considerations that tactics and prioritization could be used in their approach for initiating changes to other urban settings that face similar consideration experiences.

2. Literature Review

Efficient urban road usage is a primary focus in the area of transportation management and engineering, especially when taking into account that land use and infrastructure are scarce commodities on more densely populated territories. On the same segment of road, vehicles can flow in either direction-which is a source of both complexity and brilliance for optimizing efficiency. This emerging body of research emphasizes the necessity of grasping bi-directional traffic flow patterns and their impacts on an urban street network.

Yang *et al*. (2023) studied the inter-lane control and signal timing at isolated intersections for lane-free traffic under Connected and Autonomous (CAV) environments. The study uncovers the challenges in balancing bi-directional traffic flows. They show that well-coordinated signaling can greatly increase traffic flow and cut delays, particularly in cities where roads are a bottleneck. Bi-directional traffic zones exist, but Autonomous Transportation Planning Systems (ATPS) are crucial in maximizing their potential. Similarly, there are related needs to explore traffic flow/road efficiency relationships in bi-directional zones. Kang *et al*. (2024) investigated the optimization of gate control coordination signalization under advanced multi-agent deep reinforcement learning in urban traffic networks focusing on bi-directional traffic with hybrid networks coordinated in the active TSC mode. Their study demonstrates that well-designed coordination schemes can significantly benefit how a large-scale system operates. This strategy is an essential element in dealing with high traffic volumes of bi-directional zones, especially something hard to have return flow balanced on both sides.

The design of roads is a major factor in the effectiveness of the traffic on both sides. Si and Ding (2024) specifically examined the safety and efficiency of bi-directional traffic involving road users that are exposed and made possible pre-crash interventions. They suggested a collaboration-based perception system through roadside units to shield these users and let them see the system's possibilities in both safe and efficient bi-directional mode. Their study underscores the significance of the road design and the technological infrastructure in the process of optimizing traffic flow, especially in locations with a mixed traffic scenario.

However, tools like traditional fixed signal timings and restricted lane assignments of traffic primarily exist as disciplined arrangements, many times being barriers to the unpredictable character of urban traffic. Most recent works claim that adaptive and smart traffic control systems in bi-directional areas are the best way to manage road flow effectively. Nevertheless, some gaps still persist in the literature in terms of the failure of such strategies to address the long-term effects on exact road-network congestion circumstances. More studies is required however to examine the effectiveness of these strategies in various urban settings and opportunities concerning application of the fresh technologies, such as AI systems for traffic management within current urban structures.

Similarities and differences are seen concerning traffic congestion, traffic safety, and traffic management and flow patterns due to bi-directional traffic flow, especially given the current increasing urbanization and the need for sustainable transport solutions. In their study, Caliendo *et al*. (2021) noted that two-way traffic flow could create a safety and efficiency problem especially where road tunnels are involved. In their study carried out on a one-way road tunnel tube under bi-directional traffic, they found out that the bi-directional night traffic decreases the risk level to 80%-100% of that of day time. This finding stresses the importance of proper context-dependent management of bi-directional traffic in such settings.

Likewise, Rahman and Akhter (2015) suggested a real-time bi-directional traffic management system where the GPS and WebSocket are integral features. On their system, they provide for dynamic route computation which is essential for dealing with bi-directional traffic. Both authors proved that the full bidirectional communication of traffic management systems would improve the existing Traffic Management System in that, they enable real-time monitoring and management of the traffic conditions and hence increase the efficiency of the roads.

Subsequent work conducted by Plessen *et al.* (2016) involved the coordination of connected automated vehicles travelling in both directions, where the study also pointed to the need to prioritize schemes and path planning which are dynamic. Based on their results, they called for more effort and the use of effective strategies that will encourage smooth flow and deter any traffic above the carriageway in the multi-lane roads they explored in the automated vehicle environments. Moreover, Kim *et al.* (2022) are concerned about the seismic response of traffic light poles subjected to bidirectional moving loads in seismically active regions. Their study adds to previous work arguing for traffic flow directionality to be taken into consideration when designing the location of traffic management because bi-directional traffic adds more stress to structures during earthquakes.

Capuzzo *et al* (2018) in mathematical modeling proposed a model for packet success probability estimation of a LoRaWAN network traffic and where it has bidirectional traffic conditions. This study is relevant for smart city projects where IoT devices are employed to control traffic in the urban area. The model also caters for the bi-directional flow of traffic as it changes over time and offers an understanding of the channel networks for efficient traffic flow. Similarly, Rahman and Akhter (2016) have used neural networks in traffic prediction and they have proved through their studies that bidirectional traffic management systems, and traffic prediction by the usage of machine learning techniques are more efficient and improvement in road traffic can be accelerated.

The efficiency of traffic circulation in urban areas is strongly related to the performance of roads or streets when traffic is two-way. Traffic movement on bi-directional roads is even more challenging than on a uni-directional system because the traffic moves in two opposite directions on the same road. Often, many have suggested that this has contributed to congestion and delays, especially in the rush hours. Sometimes one flow eliminates other desirable flow and thus decreases lane capacity or creates a bottleneck, particularly at intersections and at narrow parts of road sections (Chu, *et al.*, 2011; He and Guan, 2012).

These results imply the need for enhanced traffic control measures to address the challenges that arise from bidirectional traffic movement. It is apparent from findings so far that bi-directional traffic flow is naturally more susceptible to producing congestion in comparison to unidirectional systems. The circumstance that there are two or more traffic flows is conducive to delay occurrence, especially, if vehicles have to make turns or cross a roadway. This congestion is further compounded by the fact that turning vehicles have to cross over the opposing traffic flow and this result in some form of conflict as well as slows down traffic flow. Compared to uni-directional systems, cooperative systems are hard to tune and can lead to inferior traffic flow, with longer times at intersections.

This is evident where the availability of road space is constrained and traffic flows are dense, normally in urban areas. Another major issue when it comes to managing bi-directional traffic is safety. The enhanced risk of head-on collisions and accidents at intersections is a major concern when handling such situations. Different studies have indicated that managing opposing traffic streams together with the presence of pedestrians and cyclists makes bi-directional roads more risky than unidirectional systems (Nur, *et al.*, 2012; Yao *et al.,* 2020). To mitigate such risks, there is a need for urban planners to consider adopting more stringent safety interventions like signal timings, turning lanes, and signs.

The environmental effects associated with bi-directional traffic flow also have profound implications. More specifically, the frequent stop-and-go patterns associated with congested bi-directional roads causes a significant rise in vehicle emissions and noise pollution. Empirical evidence from comparative studies suggests that, due to more variable speed and more frequent acceleration and deceleration, bi-directional traffic flow can lead to greater levels of carbon dioxide and particulates (Qi *et al.*, 2018). These issues have serious implications for urban areas already grappling with poor air quality and significant noise pollution levels.

Recent advances in technology, specifically Intelligent Transportation Systems (ITS), have been proposed as solutions to the shortcomings of bi-directional traffic flow as it has the capacity to dynamically adjust traffic signals, optimize available lane space, and manage real-time traffic flows in order to relieve congestion and enhance the efficiency of urban roads. Evidence from studies indicates that applying adaptive signal control and ITS in bi-directional travel flows can lead to significant reductions in travel times and improved road safety (Ma, *et al.*, 2020). Furthermore, predictive models based on machine learning, such as Bi-GRU (Bi-Direction Gated Recurrent Units), have shown promise in predicting traffic flows on roads and improving traffic management in real time (Zhang *et al*., 2021).

From reviews, it is evident that bi-directional road travel flow presents several challenges to the equitable efficiency of urban roads, such as increasing congestion, higher accidents, and negative environmental implications. Nevertheless, the continued implementation of traffic management technologies with planning methods designed to leverage these approaches may significantly alleviate these challenges. This is where emerging technologies and roadway design methods may yet have considerable future impact on improving travel flow, efficiency, and safety of bi-directional traffic flow in urban environments.

3. Research Methodology

The present study employs traffic data from all of Norwalk, CT's zones for all months in 2023. The data was a trove of statistics for traffic metrics such as: (daily flow, average speed, total travel times including free-flow vs. delay for bi-directional roads). These data were obtained using automatic traffic counters located throughout Norwalk. The systems constantly captured/recorded all traffic (bi-directional road segment + single travel direction) data in real-time continuously week-in week-out, regardless of the day of the week, and all day. As attached, I identified every road segment or zone through the city with its roadway name and ID, then marked the length of each segment (road section), as well as whether it was a traffic direction type view (or its bi-direction). Metrics: average daily traffic, segment speed time-of-day-profile parameter (speed profile), travel-time functions for congested speeds, free-flow-speed calibration factor, and vehicle operating costs.

Again, several analytical perspectives for comprehending the workings and implications of bi-directional traffic on road-space efficiency in urban settings were employed. First, some descriptive statistics to have a cursory understanding of what traffic conditions were like in each zone (average speeds, travel times, and delays) were produced. A comparative analysis of bi-directional and non-no-bi-directional zones based substantially on speed from delay and a couple of other efficiency related correlated metrics were also captured. Finally, an application with correlation analysis to have a better appreciation of relationships among various traffic characteristics (effect of road length and cubic traffic volume on delay or link speed) was done. This relationship with Pearson correlation coefficients to highlight what was most unremarkable about road efficiency in bi-directional zones was empirically processed.

This was a good way to make the findings more comprehensible since it could be visualized using a bar chart and scatter plot. This makes it easier to see the difference bi-directional traffic has on road efficiency while showing patterns within data. The city of Norwalk was used because of the wide range of bidirectional and unidirectional zones in the urban road network. Thus, it is close to an ideal dataset when exploring many scenarios. Altogether, this methodology allowed for the quantification of the effect of bidirectional travel in an urban environment on road efficiency and provides useful insights for those responsible for the management or planning of traffic control strategies.

3.1. Data Analysis

3.1.1. Statistical Summary

Table 1 Line Zone Length Statistics

Line Zone Length(miles) Summary	
Mean	0.0826887554
Standard Error	0.0005396286
Median	0.067
Mode	0.057
Standard Deviation	0.066057687
Sample Variance	0.004363618
Kurtosis	7.432202399
Skewness	2.1892439092
Range	0.672
Minimum	0.002
Maximum	0.674
Sum	1239.091
Count	14985

Table 2 Zone direction and average daily segment traffic Statistics

Zone direction (degrees) Summary		**Average Daily Segment Traffic**	
Mean	158.1311311311	Mean	577.4348348348
Standard Error	0.8271265857	Standard Error	17.7735077627
Median	166	Median	23
Mode	3	Mode	0
Standard Deviation	101.2512407652	Standard Deviation	2175.7125750424
Sample Variance	10251.8137564954	Sample Variance	4733725.20919756
Kurtosis	-0.8776479257	Kurtosis	49.1506458948
Skewness	0.2531931955	Skewness	6.4073764232
Range	360	Range	26477
Minimum	0	Minimum	0
Maximum	360	Maximum	26477
Sum	2369595	Sum	8652861
Count	14985	Count	14985
	0		0
vehicle miles of travel		Vehicle Hours of Delay	
Mean	42.3100447144	Mean	2.4906613226
Standard Error	1.679398689	Standard Error	0.2902270035
Median	1.27	Median	0.75
Mode	0.01	Mode	0
Standard Deviation	205.5737660116	Standard Deviation	6.4831801659
Sample Variance	42260.5732721929	Sample Variance	42.0316250638
Kurtosis	270.3720058303	Kurtosis	71.3672518495
Skewness	13.1403087171	Skewness	7.3626538721
Range	7446.05	Range	85.3
Minimum	0	Minimum	0
Maximum	7446.05	Maximum	85.3
Sum	633973.71	Sum	1242.84
Count	14984	Count	499
			0

Table 3 Regression Statistics

Regression Statistics	
Multiple R	0.6570077973
R Square	0.4316592457
Adjusted R Square	0.430515703
Standard Error	4.892478968
Observations	499

Table 4 ANOVA Table

ANOVA					
	Df	***SS***	***MS***	***F***	***Significance F***
Regression	1	9035.3831069541	9035.3831069541	377.4753851865	5.69E-63
Residual	497	11896.3661748094	23.9363504523		
Total	498	20931.7492817635			

Table 5 Intercepts

	Coefficients	***Standard Error***	***t Stat***	***P-value***	***Lower 95%***	***Upper 95%***	***Lower 95.0%***	***Upper 95.0%***
Intercept	-0.0062907522	0.2539402711	-0.0247725662	0.9802463164	-0.5052195478	0.4926380435	-0.5052195478	0.4926380435
Average Daily Segment Traffic (StL Volume)	0.0009344187	0.0000480946965837257	19.4287257736	5.69011479547221E-063	0.0008399247	0.0010289127	0.0008399247	0.0010289127

3.1.2. Multiple R

This is the Pearson correlation coefficient value. It indicates how strong the linear relationship is. A value of 0.65 indicates a fairly strong correlation between average daily segment traffic and vehicle hours of delay.

3.1.3. R Square

This is called the coefficient of determination. It is gotten by squaring the R values. It tells how much variance the dependent variable (vehicle hours of delay) can be accounted for by the independent variable (Average daily segment traffic). We can say that 43% of the vehicle hours of delay can be accounted for by the Average daily segment traffic. The remaining percentage is caused by other factors like Average segment speed, free flow speed, and Average segment travel time.

3.1.4. Adjusted R Square

This takes into account the number of independent variables (Average daily segment traffic) in the analysis and corrects for any bias.

3.1.5. Standard error of regression

This is the Average distance that the observed values fall from the regression line. My standard error is 4.89. This means on average, my observed value is 4.89 from the regression line.

- Observation: This is the number of subjects or data points in the test. I had 499 data.

3.1.6. ANOVA Table

The significance F is the P-value for the regression model. When the p-value is greater than or equal to 0.05, the null hypothesis is rejected and the alternative Hypothesis is accepted. Here my p-value is 5.69E -63, so the literary relationship is significant.

The intercept is where the regression line or line of best fit crosses the y-axis when the value of X is zero. For simple linear regression, it is represented by the formula below:

$$Y = mx + b$$

Where Y is the predicted variable, m is the slope, x is the independent variable and b is the slope. For our result, the predicted Y value is 0.000934

4. Regression Results

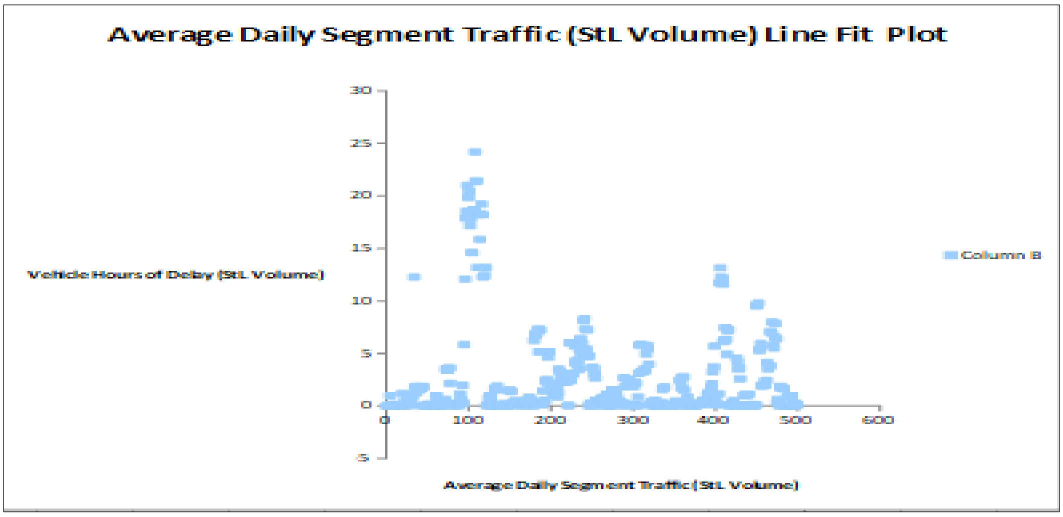

Figure 1 Regression Results for average daily segment traffic scatter plot

4.1. Efficiency Metrics

Table 6 Efficiency metrics table

Zone is Bi-Direction	Travel Time per Mile	Delay per Mile	Capacity Utilization	Avg Segment Speed (mph)	Overall Efficiency Score
FALSE	285.282	8.804817	25.54064	13.83664	280.2502
TRUE	213.6254	7.347728	19.27981	19.10914	201.864

This sheet presents efficiency metrics for bi-directional and uni-directional zones. The plots show a comparison of these metrics.

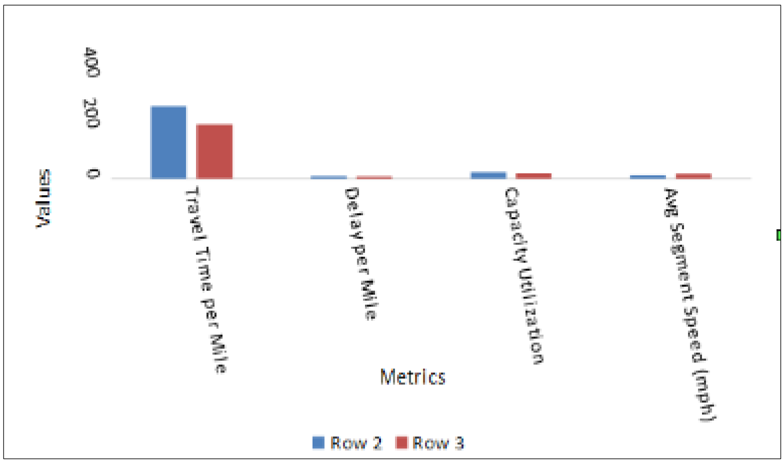

Figure 2 Uni-directional zones

4.2. Residual Plot

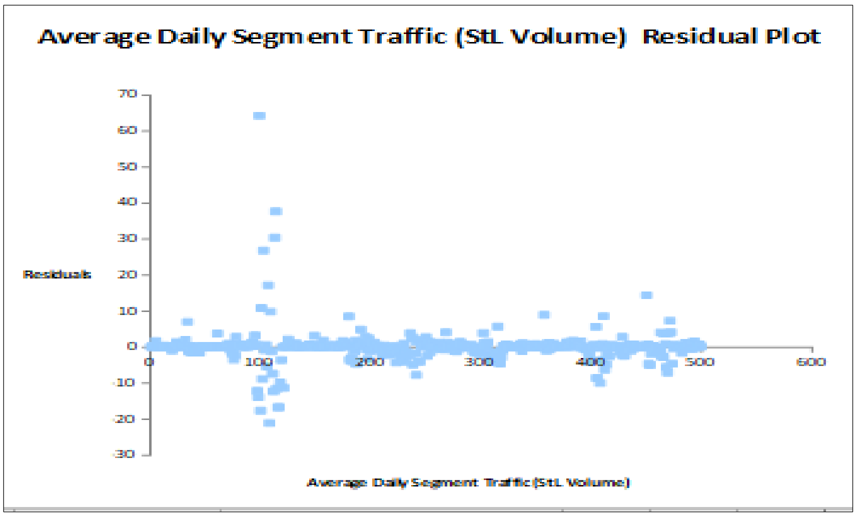

Figure 3 Bi-directional zones residual plot

A residual is the distance between the actual data point and the line of best fit. A standard residual is the residual divided by an estimate of its standard deviation. It is used to identify potential outliers in the sample. The scatter plot above has the dependent variable on the X-axis (vehicle hour of delay) and the independent variable on the Y- (average daily segment traffic). Residual plots are useful when assessing homogeneity of variance, which is an assumption of the linear regression test. The standard residual is the residual divided by an estimate of its standard deviation. They are useful when trying to identify potential outliers in the sample. Generally, any standard residual greater than plus or minus three is considered an outlier. Some of my standardized residuals are outliers as seen in the table and scatter plot

4.2.1. Interpretation of Summary Statistics

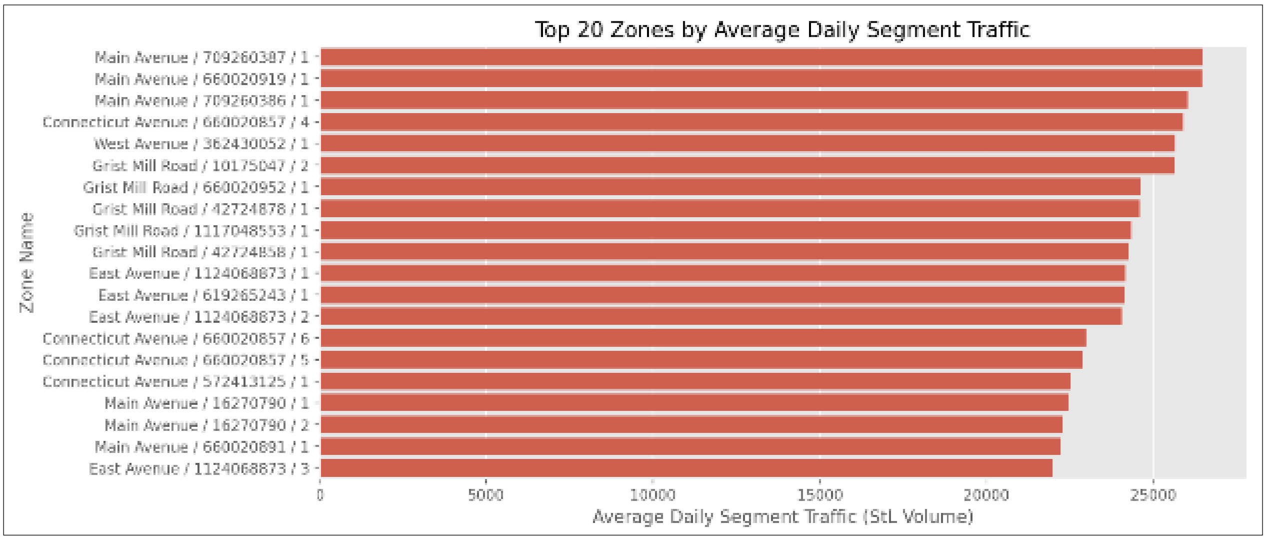

Figure 4 Top 20 zones by average daily segment traffic

This bar chart ranks the Top 20 Zones by Average Daily Segment Traffic (STL Volume), showing the most trafficked road segments in the area. This chart highlights the most heavily trafficked road segments, emphasizing the dominance of a few key avenues.

4.3. Key Points:

- X-Axis: represents the average daily segment traffic (STL volume), which indicates the number of vehicles passing through each segment daily.
- Y-Axis: Lists the Zone Name, with each zone represented by a unique identifier (e.g., "Main Avenue / 709260387 / 1").
- Top Zones: The zones with the highest daily traffic volumes appear at the top. For instance:
- Main Avenue / 709260387 / 1 show the highest volume, followed by other segments on Main Avenue and Connecticut Avenue.
- Several segments of Grist Mill Road and East Avenue are also consistently high on the list.
- Uniformity in High Traffic Zones: The chart indicates that a few key roads, like Main Avenue, Connecticut Avenue, and Grist Mill Road, dominate traffic flow. This could be due to their importance as major thoroughfares.
- Traffic Distribution: The similar bar lengths show that these top zones have close traffic volumes, with minimal differences among the most heavily trafficked segments.

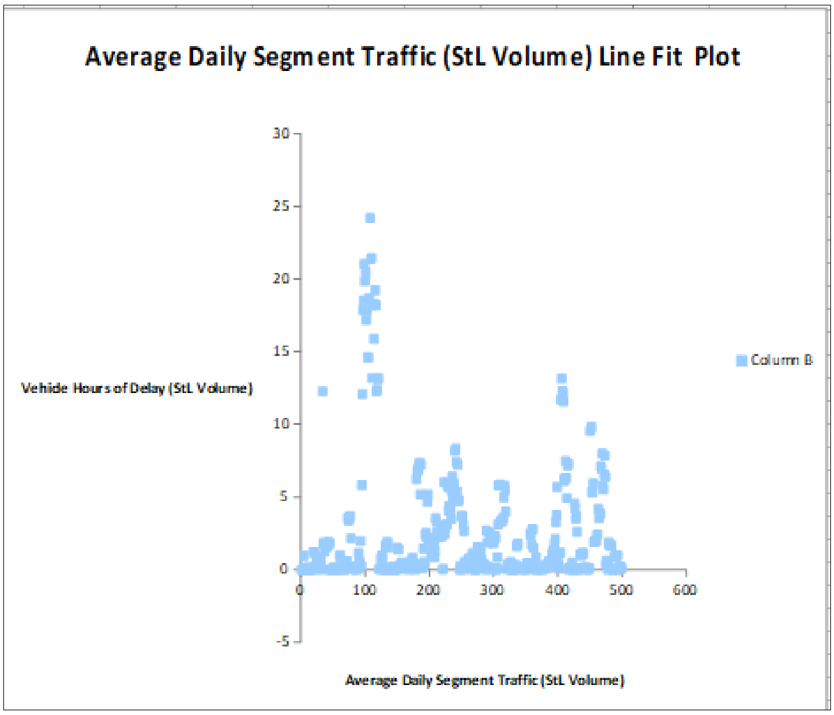

Figure 5 Vehicles hours by average daily segment traffic

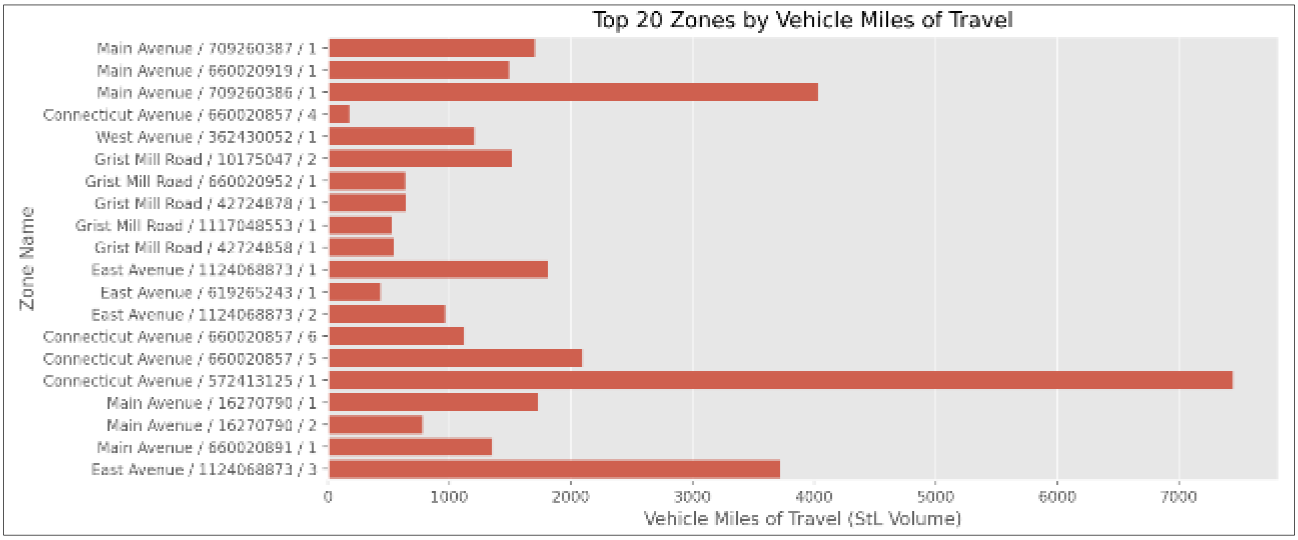

Figure 6 Zones per vehicles miles of travel plot

This chart visualizes the top 20 zones based on Vehicle Miles of Travel (VMT), showing which areas experience the highest volumes of vehicle travel.

Key Points

- *Horizontal Bar Chart:* The x-axis represents the Vehicle Miles of Travel (VMT) in STL volume, while the y-axis lists the zone names, each followed by a unique identifier (zone code) and the number of entries.
- *Zone Names and Volumes:* The bars illustrate the VMT for each zone, showing that certain zones like "Main Avenue" and "Connecticut Avenue" have notably higher volumes compared to others.
- *Comparison Across Zones:* The longest bars (e.g., "Connecticut Avenue/660020857/4") indicate the zones with the highest VMT, which suggests these areas experience the most traffic, possibly due to high population density, major roadways, or economic activity.

- Repetition of Zone Names: Multiple entries for the same street (like "Main Avenue" and "Grist Mill Road") indicate that different segments or sections of these streets are analyzed separately, reflecting differences in travel volumes across those sections.

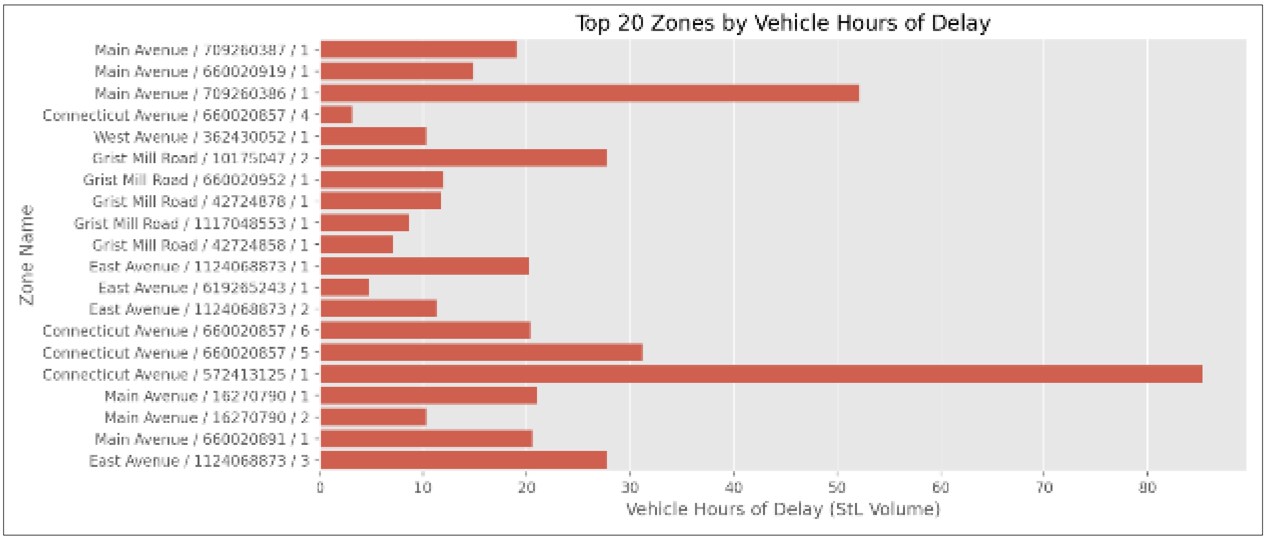

Figure 7 Zones per vehicle hours of delay

This chart visualizes the top 20 zones based on vehicle hours of delay, showing which areas experience the highest volumes of vehicle delay.

Key Points

- *Horizontal Bar Chart:* The x-axis represents the Vehicle Hours of Delay in STL volume, while the y-axis lists the zone names, each followed by a unique identifier (zone code) and the number of entries.
- *Zone Names and Volumes:* The bars illustrate the Vehicle Hours of Delay for each zone, showing that certain zones like "Main Avenue" and "Connecticut Avenue" have notably higher volumes compared to others.
- *Comparison Across Zones:* The longest bars (e.g., "Connecticut Avenue / 572412135 / 1") indicate the zones with the highest hours of delay, which suggests these areas experience the most traffic, possibly due to high population density, major road Avenue/572412135/1y.
- *Repetition of Zone Names:* Multiple entries for the same street (like "Main Avenue" and "Grist Mill Road") indicate that different segments or sections of these streets are analyzed separately, reflecting differences in travel volumes across those sections.

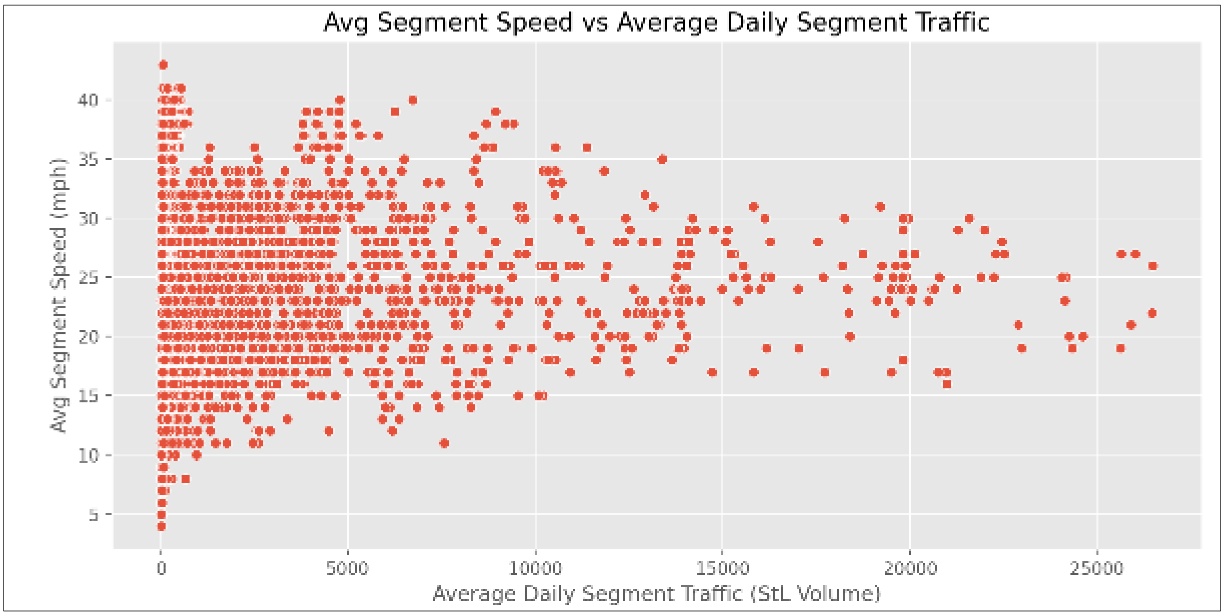

Figure 8 Scatter plot for average segment per average daily segment traffic

This scatter plot compares the average Segment Speed (mph) against the Average Daily Segment Traffic (STL Volume) for different road segments.

Key Points

- X-Axis: represents the Average Daily Segment Traffic (the number of vehicles travelling on each road segment per day).
- Y-Axis: This represents the average segment speed in miles per hour.
- Data Points: Each dot represents a unique road segment. The density and distribution of the dots provide insights into the relationship between speed and traffic volume.

Observations

- High Concentration on the Left: There's a significant cluster of points on the left side of the graph (low daily segment traffic), which generally have a wide range of speeds from 10 mph to over 35 mph. This suggests that in areas with lower traffic, speeds vary widely.
- Speed Plateaus: The plot shows that even as traffic increases, most segments still maintain average speeds between 2035 mph.
- Outliers: There are some outliers with high traffic volumes (above 10,000 STL volume) but lower speeds, reflecting segments where congestion or other factors may be limiting vehicle speed.

This scatter plot reveals that most segments with lower traffic volumes experience variable speeds, while heavily trafficked segments often maintain consistent but lower speeds, likely due to congestion. The plot helps in understanding the relationship between traffic density and average speed across different road segments.

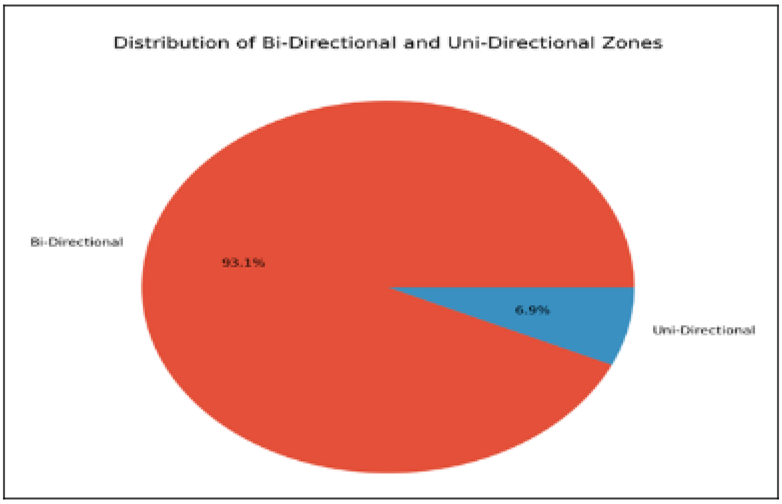

Figure 9 Pie chart showing bi- directional and uni-directional zones

The pie chart shows the distribution of bi-directional and uni-directional zones. It indicates that:

- Bi-directional zones make up 93.1% of the total
- Uni-Directional zones account for 6.9% of the total

The chart clearly illustrates that bi-directional zones are significantly more prevalent than uni-directional zones in the analyzed area.

4.3.1. Findings and Implications

The analysis of the bi-directional vs. uni-directional traffic zones in Norwalk, CT, shows clear differences in the effectiveness of the flow of traffic through basic measures such as average segment speed, travel time, vehicle delays, and capacity utilization thus:

- Traffic Flow Efficiency: Higher average speeds and smaller delays observed in uni-directional areas indicate that traffic flows more smoothly and efficiently without the need for vehicles to constantly yield to oncoming streams. Bi-directional zones, on the other hand, have acceptable speeds but still suffer from more frequent delays and longer travel times. These observations also suggest that added complexity in managing two-way traffic often reduces the overall efficiency of the roadway system.
- Consequences of Congestion: The findings indicate that congestion is considerably more frequent in bi-directional zones, reflected in the increased vehicle hours of delay and heightened variability in travel times. This means that traffic management measures will have to be more robust in these areas to mitigate the impacts of congestion, particularly in peak conditions when the interaction between conflicting streams of traffic is most intense.
- Utilization of Road Capacity: Uni-directional zones seem to be more efficient in utilizing the capacity of roads, carrying higher volumes of traffic or vehicle miles traveled. The probable reason for this increased efficiency may be attributed to fewer interferential directions of traffic flow, hence streamlining the flow of vehicles better. The lesser capacity utilization found in bi-directional zones may suggest that those thoroughfares are more susceptible to bottlenecks, especially at intersections and curves around which different directions of flow would play their way out.
- Implications for Strategy: The results of this analysis indicate the necessity of targeted interventions in bidirectional zones to improve traffic flow and reduce congestion. Probable interventions may include optimization of timings at traffic signals, design changes for intersections to reduce conflicts between opposing traffic streams, and possibly the conversion of selected bidirectional roads to uni-directional flow when feasible. Such could increase road efficiency, reduce delays, and consequently improve the quality of driving through roads in urban areas like Norwalk, CT.

In other words, the two-way flow scheme along Norwalk, Connecticut, may contribute to enhancing roadway efficiency. The scheme tends to provide higher speeds and lower travel times as the traffic volumes and vehicle miles travelled increase. The much smaller growth in vehicle hours of delay compared with growths experienced in traffic volume helps lend some credence to this view that, under specific conditions, a two-way flow scheme may work. However, problems associated with bi-directional zones outweigh their advantages, mainly in the efficiency aspect that stipulates maintaining efficient road use with traffic flow in opposite directions very problematic.

This will further empower it to enhance the traffic flow, optimize the use of road capacity, and conduct a comprehensive analysis of the causes of congestion and delays in bi-directional zones. These interventions will keynote ways to enhance the overall efficiency of the urban transportation system while flexibility supported by the both-way flow shall not harm road performance in any way.

5. Discussion

Traffic management in urban settings is, in reality, very complicated as the management involves vehicle movement interactions for maximum efficiency in road usage, especially considering the need for two-way traffic. Current developments indicate that machine learning in predictive analytics has been successfully used in forecasting real-time traffic to enhance vehicle flow in vast cities. Shetty *et al,* (2024) emphasize that machine learning models, specifically Gated Recurrent Units (GRU), can be utilized in the prediction of traffic patterns. This will enable planning authorities to come up with better strategies for flow management with the aim of reducing congestion and improving efficiency on roads.

Among the key data needed for traffic signal timings optimization and in developing new routing paths, especially in metropolitan areas, is travel time information. Tang *et al* (2024) bring a case of the advantages that are in here in Markov Chain models, about naturalistic data collection on the conditions of taxi services. Such information allows the making of big decisions that benefit urban traffic managers, who would indeed rely on such evidence-based feedback in the pursuit of, among other implementations mentioned earlier, the development of routing strategies citywide. Among those include: ongoing evaluation of roadway signal planning, rate reduction incentive programs, and downtown congestion toll initiatives-all several proactive measures against transportation challenges rather than mere alleviations. Particularly, it is very complex and demanding to manage the flow of vehicles in variable traffic conditions defined by variable bi-directional areas.

New vehicular network protocols, like UMBBFS routing protocols, will improve message dissemination under emergency conditions and will manage traffic above the urban environments. Albeyar *et al*. (2024) notes that, V2X technologies, enabled by 5G create safety in roadways and operational efficiencies of traffic because this technology makes it possible to communicate immediately between vehicles and the management of traffic lights. This is of much greater relevance when managing bi-directional traffic, where a real-time response helps avoid congestion. Other important milestones include road capacity re-allocation using intelligent systems. Zhu, *et al* (2024) explains that, shared intelligence dynamically shares road capacity and therefore enhances the efficiency of urban transportation systems. This technology may be useful in handling the flow of bi-directional traffic; for example, it is important that speed facilitates the smooth movement of vehicles without congestion.

Furthermore, collaborative intelligence enhances the real-time redistribution of road capacities to improve operation efficiency in urban road networks (Zhu *et al.,* 2024). It may be able to mitigate some of the issues with bi-directional zones, which divide road space between conflicting flows of traffic by varying the amount of road space given over to different types of users and responding to real-time changes in demand. It needs to be ascertained how this emerging class of vehicles would impact the dynamics of traffic by going with increasing efficiency in road maintenance, along with emergency response units and huge trucks.

Through methods like agent-based simulations, Sun *et al.* (2024) research factors including medium-length special vehicles, and city traffic, impact the dynamics to develop procedures that allow for the least disturbances caused by multiple types of transportation-including continuous bi-directional urban transport zones.. The use of such models enables traffic managers to devise methods and allocate resources wherein the needs of the selected vehicles may be satisfied while minimizing the general inefficiency in the flow of traffic.

6. Conclusion

The most important finding from this study is that two-way flow appears to have large effects on the performance of urban roads in congestion and travel time variability. Most of the bidirectional segments in Norwalk, CT, have lower speeds with increased delay compared with unidirectional sections, indicating that management of two-way traffic actually degrades overall road system performance. The analysis highlights the high impact on the output of these key variables: roadway configuration, traffic density, and extension of the zone.

Targeted interventions should be given to optimize the overall capacity of the roads since the congestion on the roads is high. The study calls for the improvement of traffic signal timings and reconfiguration of signalized intersections reducing conflicts among opposing traffic streams, while some of the bi-directional roads may be reconfigured into uni-directional traffic flow. Bi-directional traffic stream characteristics modeling in different urban environments with a clear distinction between peak and off-peak hours, and configuration types of roads, should thus be the focus of future studies. Of equal importance will be an in-depth study of advanced technologies for traffic management with the involvement of ITS and machine learning models regarding their potential to bring efficiency in using roads and reducing congestion in urban areas.

This realization from this study will have far-reaching implications for town planning in the management of roads and traffic. Additionally, bi-directional flow should be considered in the design of roads and traffic control strategies with respect to specific issues. It emerged from the results that while two-way streets can bear more, they are also most likely to suffer from congestion, having long-lasting impacts on urban mobility and air quality. These are some of the problems smart traffic control systems could address by better road design to contribute to the development of more efficient and sustainable urban transportation networks.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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