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Travel Patterns and Street Networks: *A Novel Visualization Methodology of City-Level Traffic Flows and Network Usability*

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Abstract

Street Networks, knitted in the urban fabric, facilitate spatial movement and control the flow of urbanization. The interrelation between a city's spatial network and how the residents travel over it has always been of high interest to scholars. Over the years, multifaceted visualization methods have emerged to better express this travel trend from small to large scale. This study proposes a novel approach to 1) visualize city-wide travel patterns with respect to the street network orientation and 2) analyze the discrepancies between travel patterns and streets to evaluate network usability. The visualizations adopt histograms and rose diagrams to provide several insights into network-wide traffic flows. The visualization of four New York City (NYC) boroughs including Queens, Brooklyn, Bronx, and Staten Island was generated for the daily traffic and the average hourly flows in the morning and evening rush hours. Then the contrasts between built-in street network topology and travel orientation were drawn to show where people travel over the network, travel demand, and finally which segments experience high or light traffic, revealing the true picture of network usability. The findings of the study provide an insight into the novel and innovative approach that can help better understand the travel behavior lucidly and assist policymakers in decision making to maintain a balance between urban topology and travel demands. In addition, the study demonstrates how to further investigate city street networks and urbanization from different diverse dimensions.

Keywords

Street Orientation, Travel Behavior, Network Usability, Rose Diagrams, Land

Use, Urban Planning, Urbanization, OSMnx

1. Introduction

Urban planning and travel patterns of city dwellers have been interrelated since the pre-historic ages. One example can be found in the ancient Mesopotamian civilization, where riverine planning influenced their travel pattern alongside ways of living, culture, trade, and social rhythms. Urban planning controls livelihood, land usage, and attractive areas where people are inclined to visit, leading to the formation of a distinct travel pattern over the city. While the spatial order structures the urban matrix, it also re-engineers the travel pattern of the residents and introduces evolution to the urban dynamics over time [1].

Understanding how street networks are designed and planned is a key for urban development and expansion. Scholars have tried to establish such an understanding through visualizing how a street network is oriented. For instance, visualization of shorelines from three Brazilian coastal cities was presented by Mohajeri *et al.* [2] using directional analysis through histograms and roses. A study of Geoff Boeing examined street networks and visualized their orientation grids through retrieving data from OpenStreetMap using concepts from graph theory and spatial analysis [3]. Such studies prove useful in decision making for urban planning as they can give a clear indication of how a city street network is planned and provide metrics of networks' topologies.

From a transportation standpoint, analyzing the usability of city street networks in terms of traffic flows is key to understanding how and where people travel. The study of travel patterns has always been the focus of transportation researchers because it influenced urban planning. Authorities and transportation operators have been investing in Information and Communication Technologies (ICT) in many cities in the last two decades to foster digitalization and bring the emergence of smart city planning [4]. Intelligent Transportation Systems (ITS) are such an example of ICT, which generates an unprecedented number of spatiotemporal datasets that could lead to a better understanding of the travel behavior of citizens in intracity spatial order [5].

Big Data generated by ITS provides both opportunities and challenges for human travel behavior research [6]. These datasets have been analyzed using various approaches to visualize and understand travel behavior. An example of such data is Origin-Destination (OD) and traffic flow data which researchers used to draw important insights into how and where people travel over a city network. Tobler expressed geographical movement using an arrow form of flow mapping between places, using the information in "from-to" tables [7]. The arrows were used to show flow directions while their widths were used to represent flow rates. The main drawback of such a methodology is that when arrows overlap, the overall visualization becomes unclear. OD data was also visualized through OD matrices by Andrienko where cells represented OD flow within regions and all regions were indicated by rows and columns of a matrix [8]. However, region to region spatial information was missing and the visualization was not intuitive [9]. Such limitation was overcome by Wood *et al.* who mapped OD vectors as cells where the geographical space was divided into a regular grid. Unlike typical OD matrices, cells in that approach reflect original geographic locations with nested areas within them [10].

With the availability of Global Positioning System (GPS) and mobile phone data, more scalability and varieties have emerged in visualizing travel behavior, making it more impeccable from various angles. Careful analysis of digital footprints from taxi GPS data is an innovative strategic medium to improve urban planning and operational decision-making [11]. In a study by Yue *et al.*, taxi trajectory data were used to understand travel demand by quantifying the attractiveness of land use. A time-dependent flow interaction matrix was developed for a better insight into urban planning and management [12]. An analysis of travel behavior was performed by Rizwan *et al.* on the Location-based social networks (LBSNs) method which uses user's social activity as LBSNs datasets [13]. Such large-scale analysis and visualization study was also done by Wang *et al.* on taxi GPS data which focuses on OD pairs and proposes a newly adapted chord diagram to express urban travel characteristics [9]. Liu *et al.* also used such massive taxi trajectory data to provide insights on travel behavior based on activity semantics and flow clustering [14]. However, these taxi trajectory approaches only considered pick up and drop off points as OD so, detecting which segments are being used is not specified. Unlike previous studies, Liao *et al.* fused taxi trajectory data and human check-in data to visualize travel behavior [15], establishing a system called VizTripPurpose but it only covered weekly data. Additionally, visualization based on mobile phone records was done by Wang *et al.* to reveal transportation corridors through Eigen lines used as discrete OD links [16]. However, the eigen line cannot represent all roads with high traffic as some roads such as inner roads may not have eigen lines, which affects the efficiency of this approach in visualizing travel patterns throughout an entire network.

The literature shows that significant effort was done to study travel patterns. Every approach comes with its advantages and drawbacks as summarized in **Table 1**. Previous research has surely brought an evolution in urban planning and management decisions. While urban planning and city street network topologies have been extensively studied, to the authors' knowledge the link between travel behavior and network topology has not been established in-depth. Considering which road segments are being used the most to travel through cities is a key to understand how and where people travel in cities. This study addresses this gap by proposing a visualization methodology that builds on that developed by Geoff Boeing [3] by adding a layer to show how many city network streets are being used to serve traffic demands. In doing so, we analyze Traffic Volume Data from

Table 1. Summary of visualization approaches from literature.

Authors	Approaches	Dataset	Helpful Aspect	Drawback
Tobler, 1987	Flow mapping through arrows.	Migration OD data	First introduced the use of arrows.	Overlapped arrows confuse visualization.
Andreinko & Andreinko, 2008	OD matrix	GPS data	Effective aggregation of movement data.	Region to region spatial information is missing.
Yue *et al*., 2009	A time-dependent flow interaction matrix	Taxi Trajectory data	Understanding pattern regarding the level of attractiveness.	Pick Up and Drop off point is taken as O & D. So, which segment is being used is not clear.
Wood *et al*., 2010	Mapping OD vector using a regular grid.	Migration Flow	Representation of region-to-region spatial information	Fails expressing OD flow change.
Wang *et al*., 2015	Using Eigen lines as discrete OD links	Mobile Phone Record	High penetration rate, wide service area.	Eigen lines are not capable of representing all streets with traffic but only those having obvious traffic.
Wang *et al*., 2019	Expressing OD characteristic through chord diagram.	Taxi GPS Data	High automation, Grasp real-time traffic situation.	Pick Up and Drop off point is taken as O & D. So, which segment is being used is not clear.
Liao *et al*., 2019	Human check-in & trajectory data fusion.	Taxi Trajectory Data	Allows understanding time-evolving trip purpose pattern.	Little Visualization capability, only covers weekly data.
Rizwan *et al*., 2020	Spatial distribution of human check-in data	LBSN data	Gives insights on human activities over space-time.	Not comprehensive. Only include recorded check-ins which may differ from actual urban flow.
Liu *et al*., 2022	Flow clustering method.	Taxi Trajectory Data	High-level activity dynamics and travel behavior are expressed on geographic context.	Pick Up and Drop off point is taken as O & D. So, which segment is being used is not clear.

NYC open dataset to visualize and quantify how and where people travel relative to the orientation of the road network in four different areas in NYC (the Bronx, Brooklyn, Staten Island, and Queens). We use the OSMnx tool [17] which retrieves data from OpenStreetMap and builds a layer to visualize travel patterns using Traffic Volume data through a python program. Alongside visualizing the travel pattern, we establish an intuitive relationship between network topology and traffic flows.

2. Methodology

2.1. Study Area

This study is carried out using data from New York City, USA. Also called New

York, this is the most densely populated city in the USA. Located at the southern tip of U.S. state (40˚42'45.86"N, 74˚0'21.5"W), it is the center of trade, culture, research, and international diplomacy. Having a population of 8,336,817 distributed over about 784 km^2 area, it is the most populous megacity. New York has five boroughs: Manhattan, Brooklyn, Queens, the Bronx, and Staten Island. This study uses traffic volume data collected from four boroughs (Brooklyn, Queens, Bronx, and Staten Island) through the open data initiative based on maximum data availability. Sketches of the street networks of the four boroughs are presented in Figure 1 along with their locations over NYC geographic map.

Figure 1. Street network sketch of (a) Queens, (b) Brooklyn, (c) The Bronx, (d) Staten Island, (e) Four study areas across NYC.

2.2. Data Description

The traffic volumes are collected hourly over entire 24-hour periods with at least a one-week continuous coverage for every road segment. As seen in **Table 2**, the counts are collected for every segment, identified in the form of a from-to (*i.e.*, directional) between every two intersections in the street network of every borough. The dataset contains approximately 20,000 count records covering the period from 2014 to 2018. The hourly traffic counts are quite useful for rush hour analysis, while the direction of travel information will help to better understand the orientations of flows throughout a network. These characteristics make the dataset very well-suited for our visualization approach.

2.3. Data Processing, Analysis, and Visualization

Figure 2 shows the workflow followed in the study to produce visualizations of the city street network usability in terms of traffic flow. The traffic volume data was first extensively explored to identify how it is structured and what

Table 2. Traffic volume count (2014-2018), NYC open data.

Count ID	Segment ID	Roadway	From	To	Direction	Date	12:00-1:00 AM	1:00-2:00 AM	…
2	70,376	3 Avenue	East 154 Street	East 155 Street	NB	9/13/2014	204	177	…
224	9,003,579	Morris Avenue	156 Street	Park Avenue	SB	9/14/2014	224	226	…
…	…	…	…	…	…	…	…	…	…

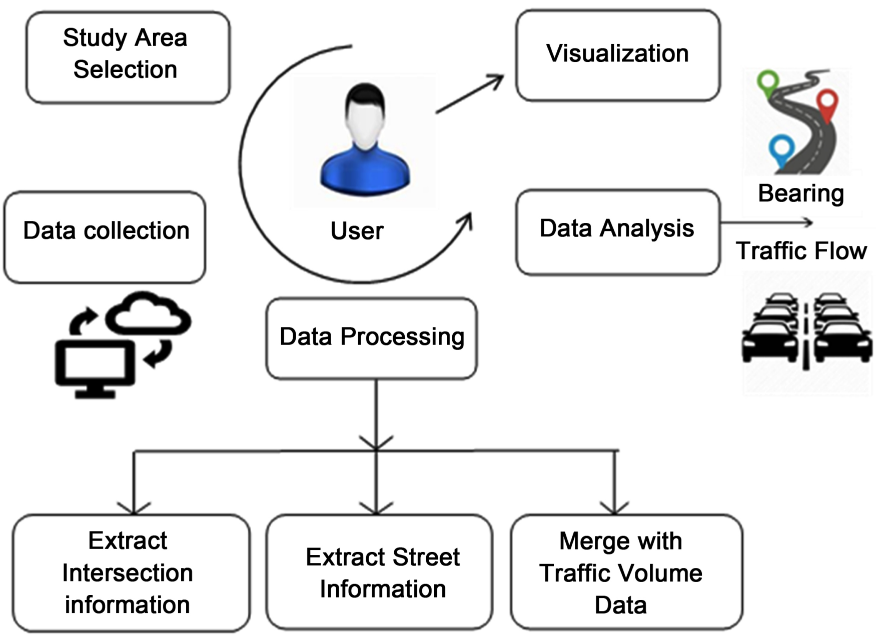

Figure 2. Framework for generating network usability visualizations.

processing steps are needed. Then, the geospatial information (coordinates) of all intersections in every borough was extracted through OSMnx. This information was then linked to the extracted traffic volume data based on the intersection IDs and the from/to information in the data. Finally, the bearings of all road segments and traffic flows were calculated to produce the proposed visualizations.

2.3.1. Extracting Intersection Information

Since the traffic volume data is formatted in a from-intersection-to-intersection format, extracting the intersection information is a key in identifying where and in what orientations people travel. To obtain the intersection information, we use the OSMnx tool [17], a newly developed tool that provides geospatial information of all nodes in a street network along with the bearings of road segments in an automated way. The tool is based on the Python platform and retrieves data from OpenStreetMaps to help visualize the street network and their information lucidly. A sample pseudo code on how data is extracted is shown in **Figure 3** algorithm.

All the intersection coordinates (excluding dead ends) within every borough in NYC were extracted in addition to the names of streets connected to every intersection. **Table 3** shows an example of the extracted intersection information.

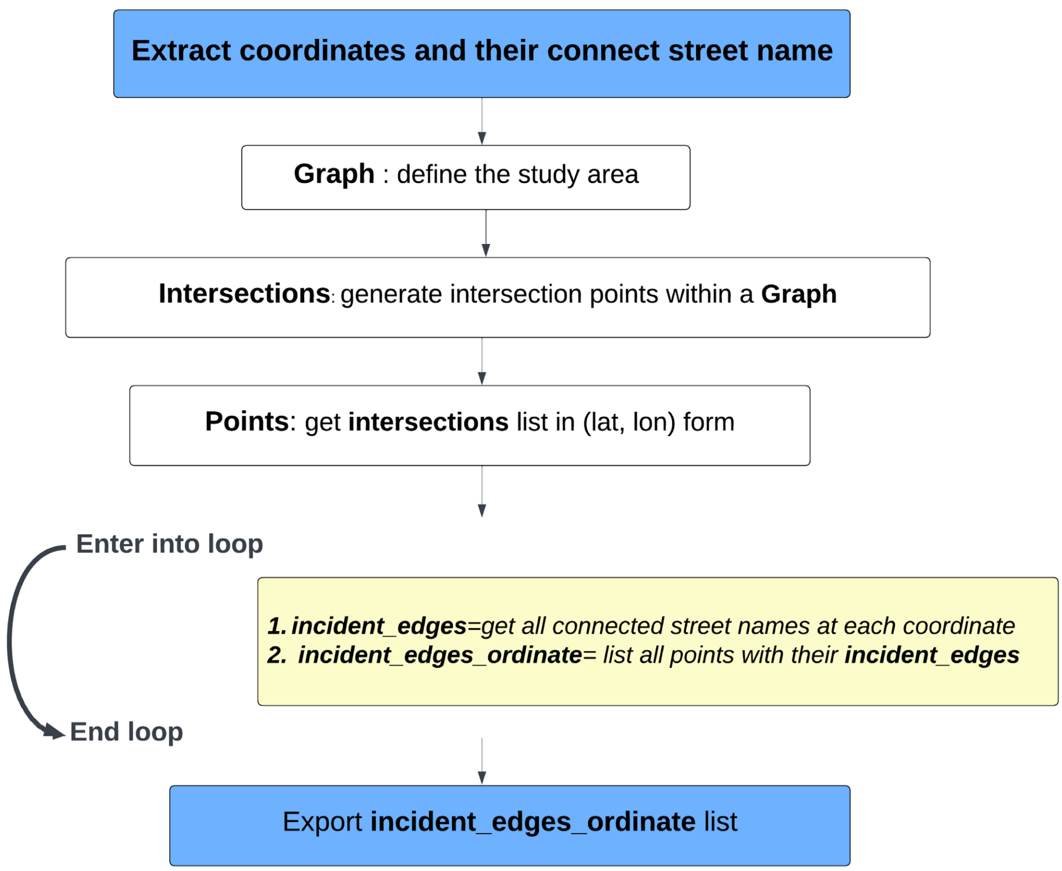

Figure 3. Intersection information extraction.

Table 3. Snapshot of intersection information and their respective connecting streets, Queens.

Intersection Latitude	Intersection Longitude	Connected Street 1	Connected Street 2	…
40.70982	−73.8345	Park Lane South		
40.70936	−73.7888	90th Avenue	172nd Street	
40.71073	−73.9186	Onderdonk Avenue	Troutman Street	
40.70887	−73.7326	223rd Street	107th Avenue	
40.70893	−73.7382	Springfield Boulevard	109th Avenue	
40.70953	−73.7964	Hillside Avenue	Merrick Boulevard	166th Street
…	…	…	…	…

2.3.2. Linking the Intersection Information with the Traffic Volume Database

The extracted intersection information was then linked to the traffic volume data based on the from/to intersection information in the traffic counts database. First, the counts database was processed to identify distinct road segments and their respective intersections. This reduced the dataset to approximately 2000 distinct segments in the four boroughs. A Python code (as described in the following pseudo-code) was developed to match the geospatial intersection information to the distinct road segments through the "From", "Roadway", "To" variables in the traffic counts dataset. The resulting data had the coordinates of each node along each segment tied to the hourly traffic counts over that segment. This process was repeated for all segments in each of the selected four boroughs. **Table 4** shows a snapshot of the merged data for Queens borough. Algorithms for matching area wise street information with traffic volume data are shown in **Figure 4** and **Figure 5**.

2.3.3. Calculation of Trip and Road Segment Bearings

As a final step before developing the visualizations, the bearings for the road segments and the traffic flows were calculated. For the road segment bearings, the OSMNx tool developed by Boeing was used. OSMNx automatically gives the bearing information for all road segments based on the coordinates of every two nodes along every small road segment [17]. This process was modified to calculate the bearings for trips. Like the bearing calculation of the road segments, the trip bearings were calculated based on the coordinates of the origin and destination intersections. Unlike road segments, trips between every origin and a destination intersection are directional (NB, SB, EB, or WB). Therefore, the trip bearing calculation process was modified to account for these directional characteristics. **Figure 6** shows how the bearings are calculated for the trips considering the quadrants they fall in and the direction of travel.

Table 4. Snapshot of the merged data for Queens.

Segment Id	Roadway Name	From	To	Direction	Origin (lat.)	Origin (lon.)	Destination (lat.)	Destination (lon.)
60,010	Sutphin Boulevard	Arlington Terrace	109th Avenue	NB	40.69248	−73.79882	40.691621	−73.798031
150,346	Merrick Boulevard	111th Avenue	111th Road	SB	40.6944393	−73.7815524	40.6938729	−73.7808579
64,444	Murdock Avenue	198th Street	199th Street	WB	40.699538	−73.756465	40.699772	−73.755579
52,092	Eckford Avenue	Tahoe Street	Raleigh Street	EB	40.670387	−73.837471	40.670186	−73.836604

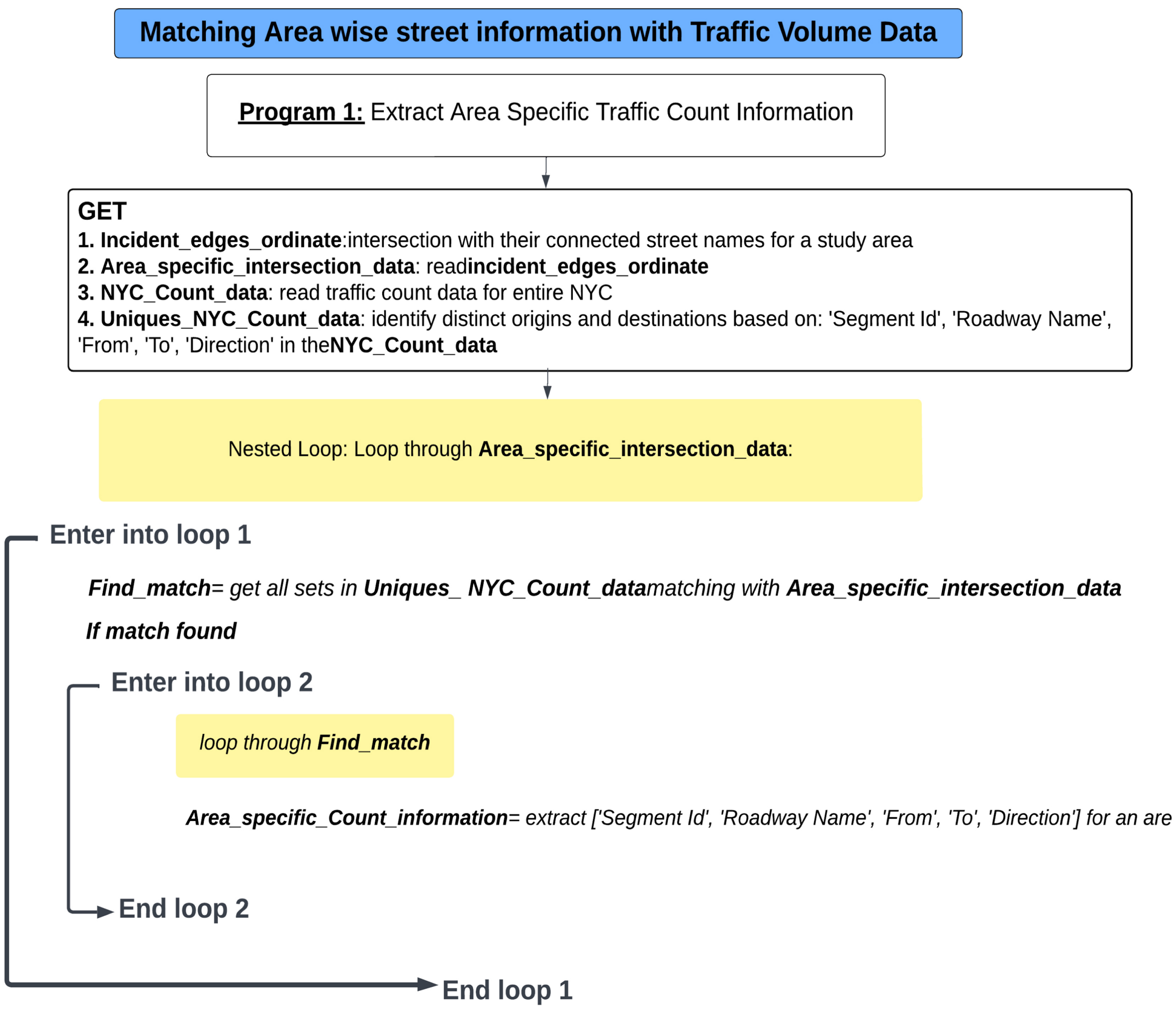

Figure 4. Algorithm 1 for matching area wise street information with traffic volume data.

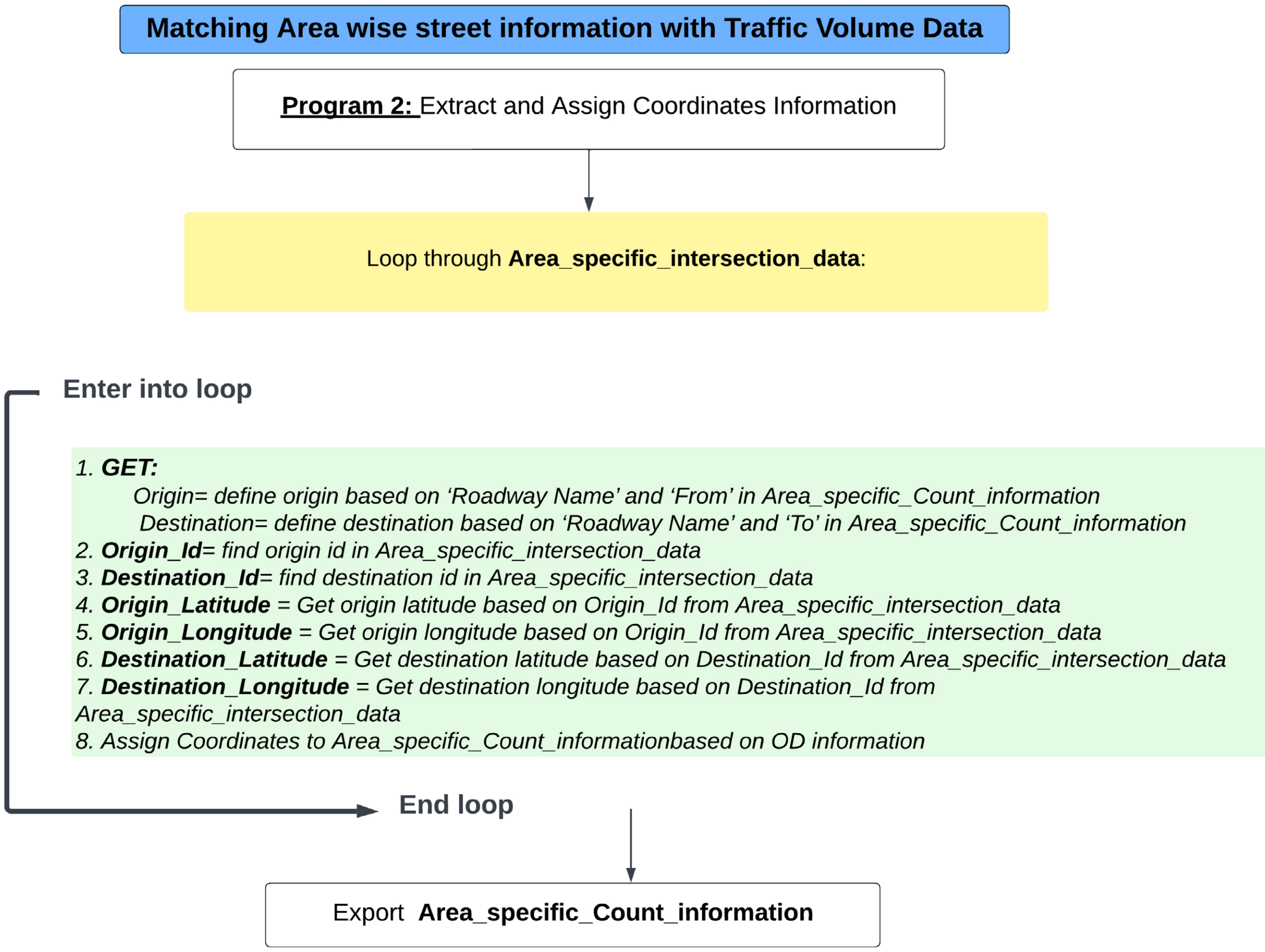

Figure 5. Algorithm 2 for matching area wise street information with traffic volume data.

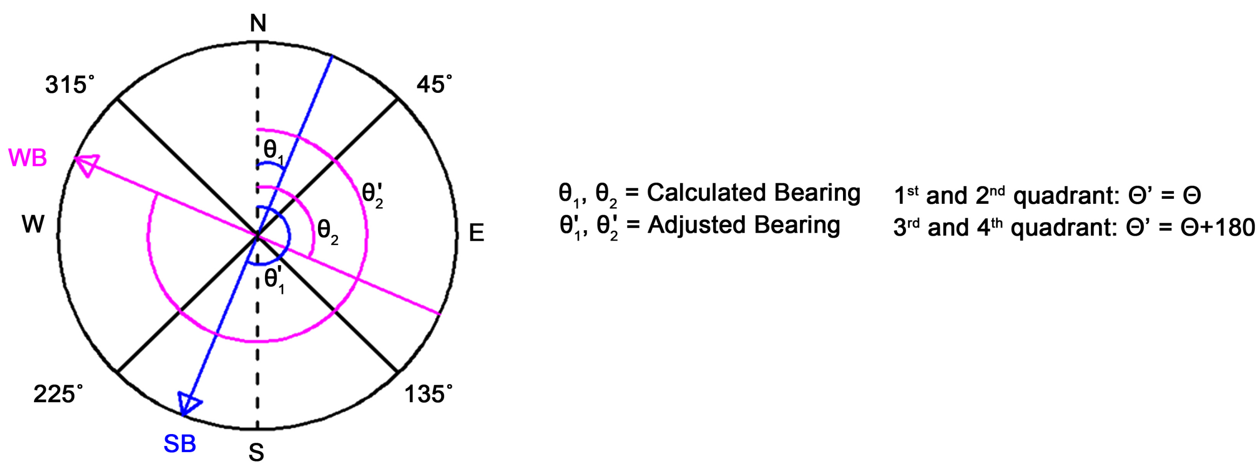

Figure 6. Trip bearing calculation (SB and WB are used as examples; Θ' = trip bearing).

2.3.4. Traffic Volume Aggregation

Upon completion of the bearing calculation, traffic volumes were extracted for one weekday and over three morning hours (7 - 10 am), and three evening hours (4 - 7 pm). These data were extracted as a sample to show how the visualization of trips works and to explain what conclusions can be drawn from it. Table 5 shows a sample of the complete dataset made ready for generating the visualization generation step.

2.3.5. Visualizing Trips on the City Network Streets

Since OSMnx produces visualizations of the city street network orientations every 12 degrees, the trips over the network were aggregated based on their extracted bearing information to display the traffic volumes in every 12-degree orientation (0˚ - 12˚, 12˚ - 24˚, 24˚ - 36˚, etc.) over the city street network. Two sets of figures were generated. The aggregated traffic flows vs the respective bearings through the bar chart first. Then, to provide a better view of the orientation, Rose diagrams were generated for the aggregated flow values for every 12 degrees. The Roses represent the core output of the visualization methodology herein to draw conclusions when compared to the respective roses of the street networks.

3. Results

Network orientation and traffic volume orientations can provide us with a deep insight into where people travel over an entire city street network. The traffic volume orientation is summarized for each of the selected four NYC boroughs in subsequent figures with their network orientations. The traffic flow visualization is represented in 3 categories: total daily flows, average hourly flows for the morning peak (average of the hourly flows counted in each peak period), and average hourly flows for the evening peak (average of the hourly flows counted in each peak period). The traffic flows for each of the three categories were aggregated and added up for all segments in each of the 12˚ bins. To explain orientations, we apply terminologies used in wind directions as seen in Figure 7.

Table 5. Sample of combined traffic volumes and bearings for queens.

Segment ID	Roadway Name	From	To	Direction	Daily traffic	Average Morning Peak (hourly)	Average Evening Peak (hourly)	Trip Bearing	Road Bearing
60,010	Sutphin Boulevard	Arlington Terrace	109th Avenue	NB	7841	514	419	325.0429204	145.0429204
150,346	Merrick Boulevard	111th Avenue	111th Road	SB	13,812	637	829	137.0867958	137.0867958
64,444	Murdock Avenue	198th Street	199th Street	WB	4736	295	296	250.7931953	70.7931953
52,092	Eckford Avenue	Tahoe Street	Raleigh Street	EB	3727	191	320	106.9959608	106.9959608
…	…	…	…	…	…	…	…	…	…

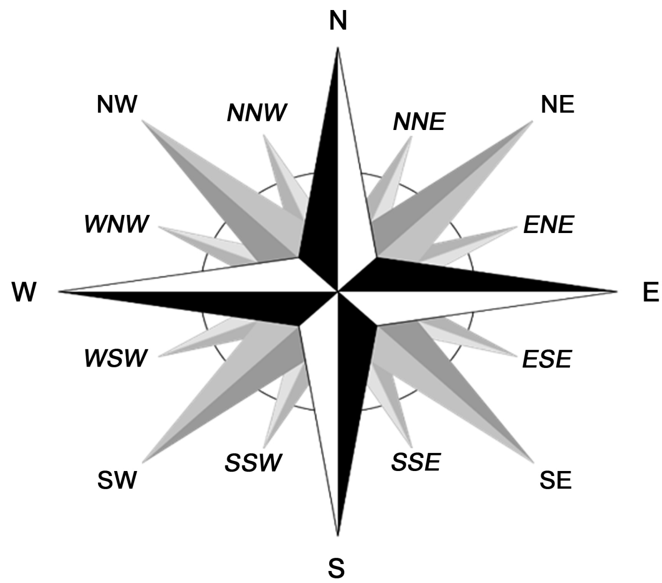

Figure 7. Wind direction terminology [18].

Figure 8 shows the orientations of the traffic flows for all the three flow categories in both the histogram and rose formats for Queens borough. The histograms show that most trips are in bins with bearings of 264˚ - 276˚, 84˚ - 96˚, 156˚ - 186˚, and 336˚ - 348˚ with descending order. When looking at the roses, it becomes clearer that most trips are in the West direction, followed by the East, southeast, then northwest directions, respectively. To make sense out of these visualizations, especially the roses, the city street network roses for Queens borough were generated through the OSMNx tool and presented in **Figure 9**. The figure shows that Queens's street network is mainly oriented in the NNW (North-North West), ENE, SSE, and WSW directions. Most of the streets have bearings between 50 to 80, 240 to 252, 150 to 165, 230 to 260, and 325 to 340 degrees. When comparing the orientation of the street network to the travel patterns, most of the traffic travels in directions that do not completely match the orientation of most streets. While there is a match between the flows in the SSE and NNW and the portion of the street network oriented in these directions, most flows have E-W orientation which does not match the WSW orientation of a major portion of the street network. For example, in 240˚ - 252˚, the traffic is not as much compared to the huge amount of street it contains many of Queens's streets do not experience as much traffic. The opposite event takes place in directions like 84˚ - 96˚ where they experience a comparatively high level of trips but have fewer streets. The figures also show that there is no significant change between the AM and PM peaks, which indicates that many of Queens's streets may be busy all day long. Nonetheless, some streets may see an increase or decrease in the traffic flows between the morning and evening periods. This is clear for the streets in the EbS direction that experience increase in the traffic flows to close to ~10,000 veh/hr in the evening compared to close to

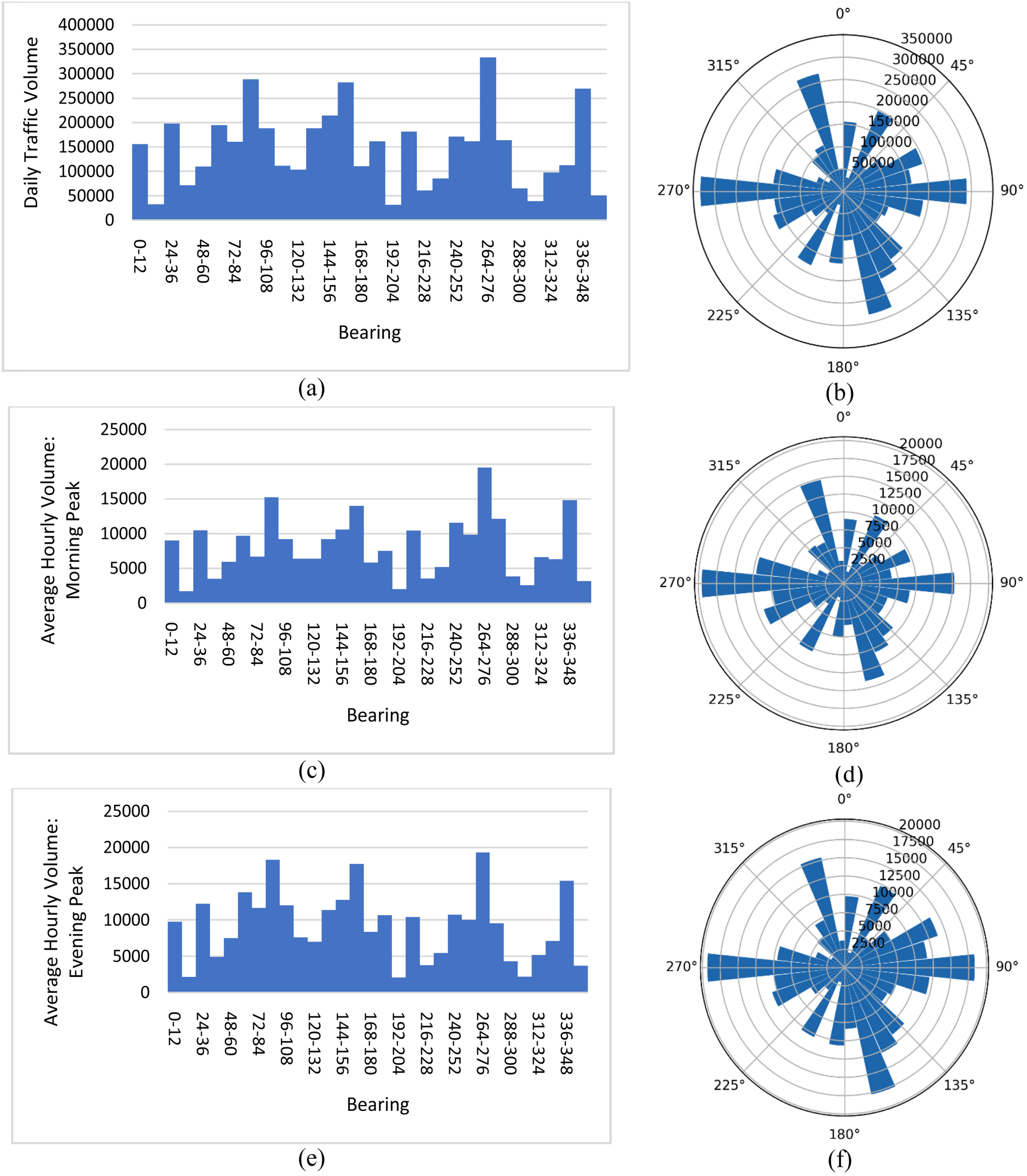

Figure 8. Traffic flow orientation: daily traffic ((a), (b)), average hourly morning peak ((c), (d)) & average hourly evening peak ((e), (f)) of Queens.

~7000 veh/hr in the morning. On the other hand, the streets in the WbN orientation have higher flows in the morning (~10,000 veh/hr) compared to the ~7000 veh/hr in the evening. These numbers show clearly that traffic demands are reversed in the PM compared to AM peak for those directions.

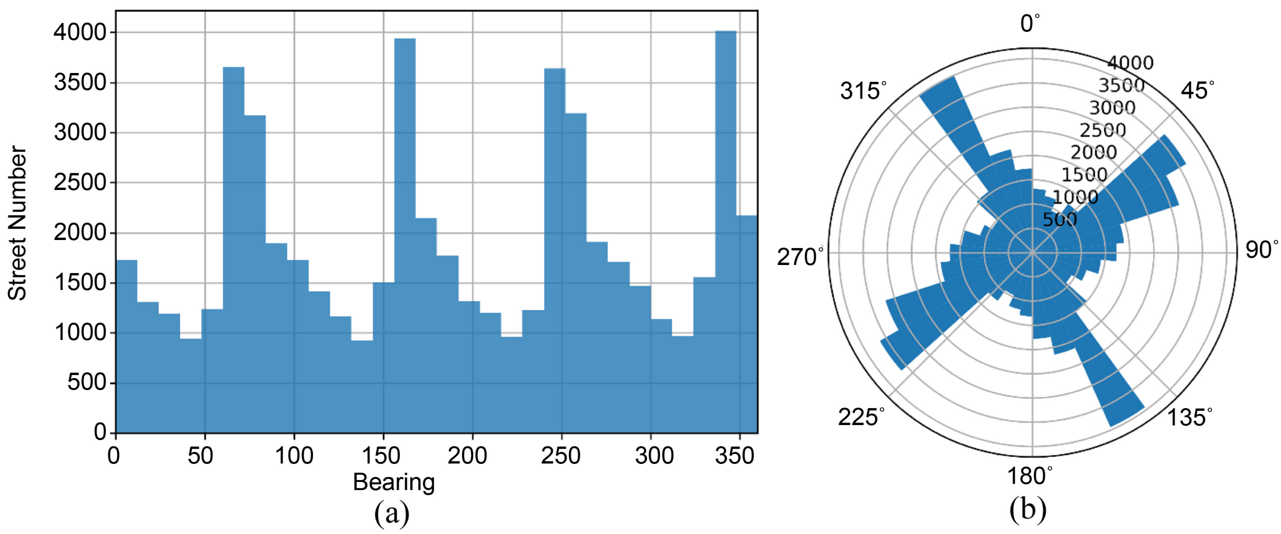

Figure 9. Street network orientation of Queens ((a), (b)).

Brooklyn borough's flow data is presented in **Figure 10** with the categorized histograms and roses. It shows that majority of traffic flows are with bearings 348˚ - 360˚, 168˚ - 180˚, 72˚ - 84˚, and 252˚ - 264˚. The Roses show clear traffic demand in these four directions: NNW, WSW, SSE, and ENE. When comparing these traffic demands to the street network orientation of Brooklyn in **Figure 11**, it is evident that unlike Queens most of the traffic demand matches how most streets in Brooklyn are oriented but with a slight inclination for the traffic flows to the N-S and E-W lines indicating that there is still a slight mismatch between where people travel the most and where the majority of streets are built. For example, many built-in streets are observed at the direction of 348˚ - 360˚, 168˚ - 180˚, 72˚ - 84˚, and 252˚ - 264˚ which experience heavy traffic too. However, a significant number of streets are also observed in 36˚ - 48˚, 216˚ - 228˚, and 300˚ - 312˚ where fewer trips are found in comparison to the numbers of streets, indicating less usability of roads in these directions. Whereas, in 144 - 156- and 324 - 336-degree directions, fewer streets experience high traffic. When looking at peak hours, PM peaks are higher in the SSE and ENE directions indicating that streets in those directions experience higher demands in the evening compared to the morning. In the 72˚ - 84˚ and 168˚ - 180˚ direction, the average hourly flow is approximately 15,000 to 20,000 veh/hr in the morning in comparison to 20,000 - 25,000 veh/hr in the evening rush hours. It clearly shows a higher travel demand of urban residents in the evening than morning in the same direction. Other than that, most of the other streets show slight changes between the morning and evening peaks.

In the Bronx borough (**Figure 12** and **Figure 13**), a clearer scenario of a mismatch can be seen as depicted in **Figure 13**, the street network in the Bronx borough is to some extent uniform in all directions with a clear cluster of built streets in the WbN-EbS directions. On the other hand, the traffic flows are not as uniform with most of the traffic traveling on streets in the ESE, SSW, WNW, E,

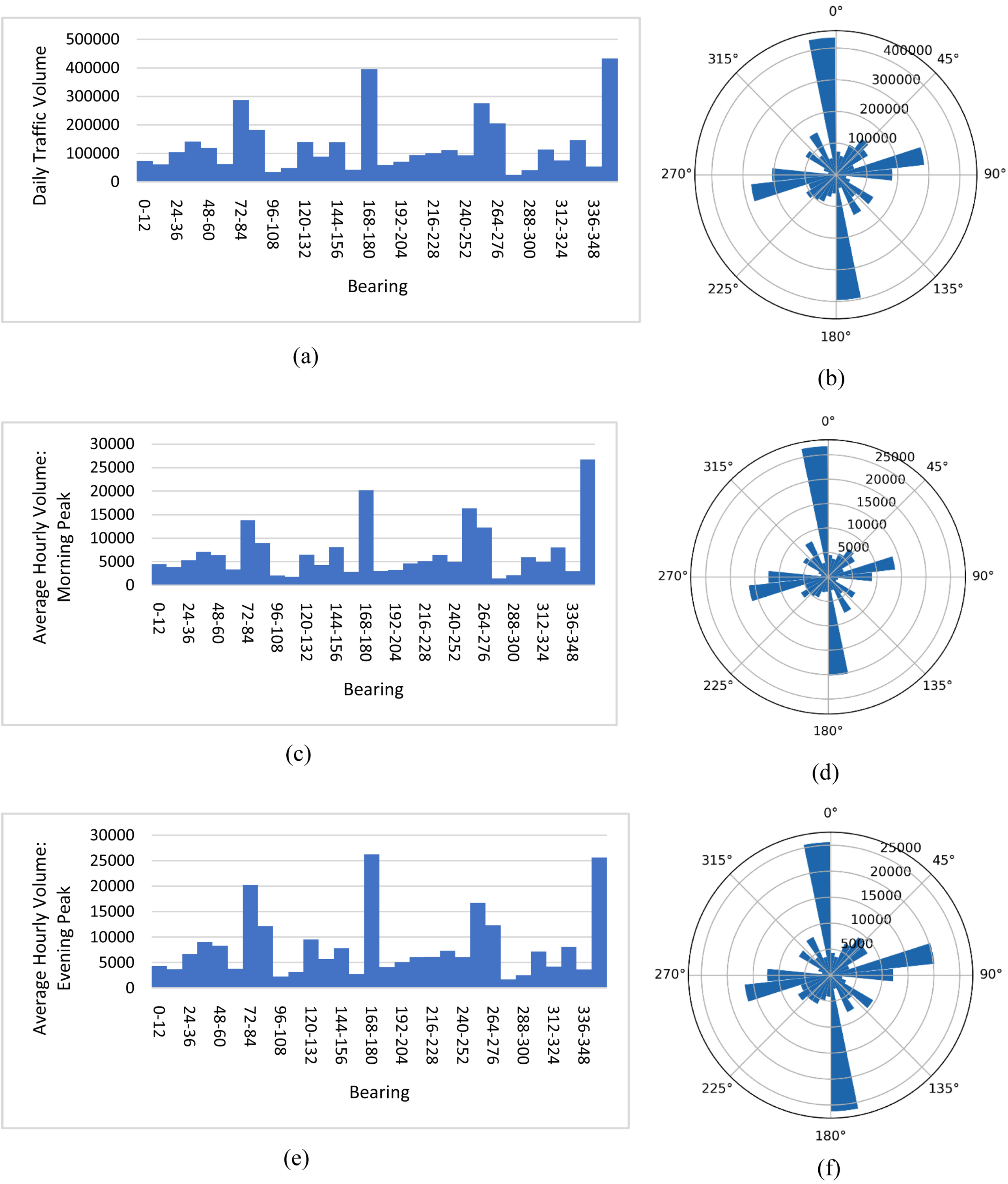

Figure 10. Traffic flow orientation: Daily traffic ((a), (b)), Average hourly morning peak ((c), (d)) & Average hourly evening peak ((e), (f)) of Brooklyn.

and W directions. Yet, traffic is distributed in all directions indicating that the way the street network is oriented has an impact on where people travel, but with significantly different levels. In other words, while traffic is distributed in

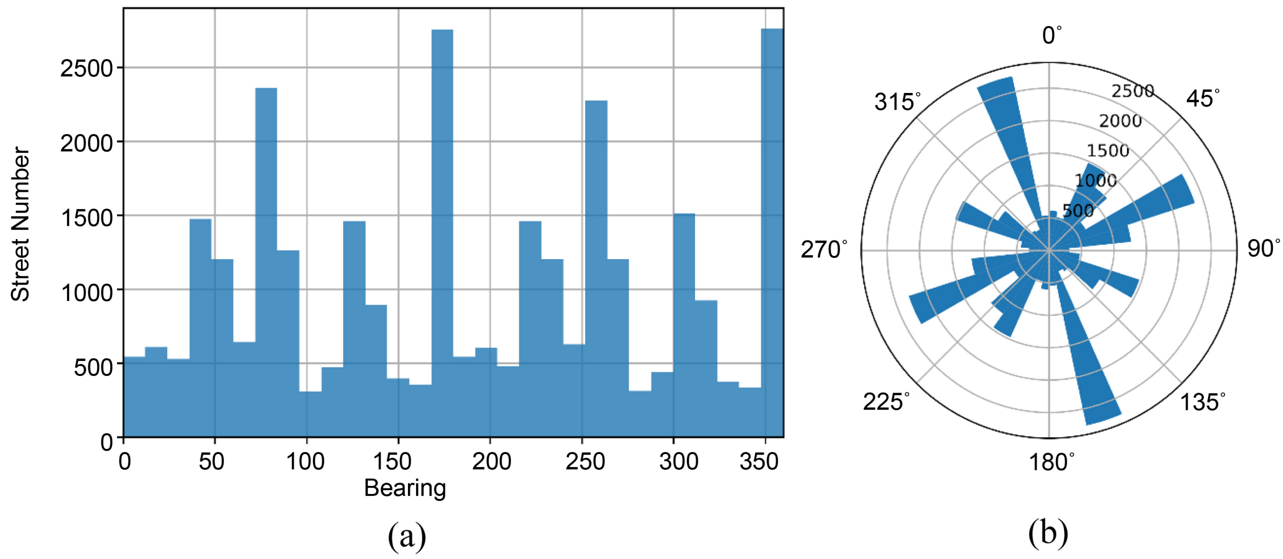

Figure 11. Street network orientation of Brooklyn ((a), (b)).

all directions as the street network, many roads experience very low traffic demand compared to those in the ESE, SSW, WNW, E, and W directions. For example, in the bins of 348˚ - 360˚, there are many built streets which are apparent from **Figure 13**. However, there is not that much traffic traveling on those streets showing less usability of streets oriented in that direction. The opposite scenario can be observed in the 264˚ - 276˚ direction where the number of streets is not as much compared to the high trips experienced by those streets. These observations apply to the daily traffic, AM, and PM peaks, with some differences in demand for some streets in the PM compared to the AM peak. As an example, the streets in the SSW direction have higher PM flows (~14,000 veh/hr) compared to the AM peak (~10,000 veh/hr). A closer look at the rush hour pattern tells us that the evening peak flow has an upper hand on the morning peak flow, similar to the travel behavior observed in Brooklyn. In most of the directions (*i.e.*, 12˚ - 24˚, 84˚ - 96˚, 288˚ - 300˚, 348˚ - 360˚, etc.), PM peaks are higher than the AM peaks, showing how people travel over the network more during the evening than in the morning.

The result of comparing the traffic flows with the street network orientation in Staten Island is not very much different from that of Bronx, as can be seen in **Figure 14** and **Figure 15**. The street network in Staten Island is to a far extent uniformly oriented in all directions with clear clusters of streets in the ESE and WNW directions, as well as in the ENE and WSW directions. However, when looking at where traffic is mostly present, streets in the E, W, and EbS directions are the most traveled in the Borough of Staten Island. A slight mismatch is seen in direction 300˚ - 312˚, where high numbers of streets are present which are less usable as they do not experience many trips. When comparing AM and PM peak traffic flows, the figures show that the Staten Island streets experience higher traffic flows in the morning compared to the evening in N-NE regions, and in

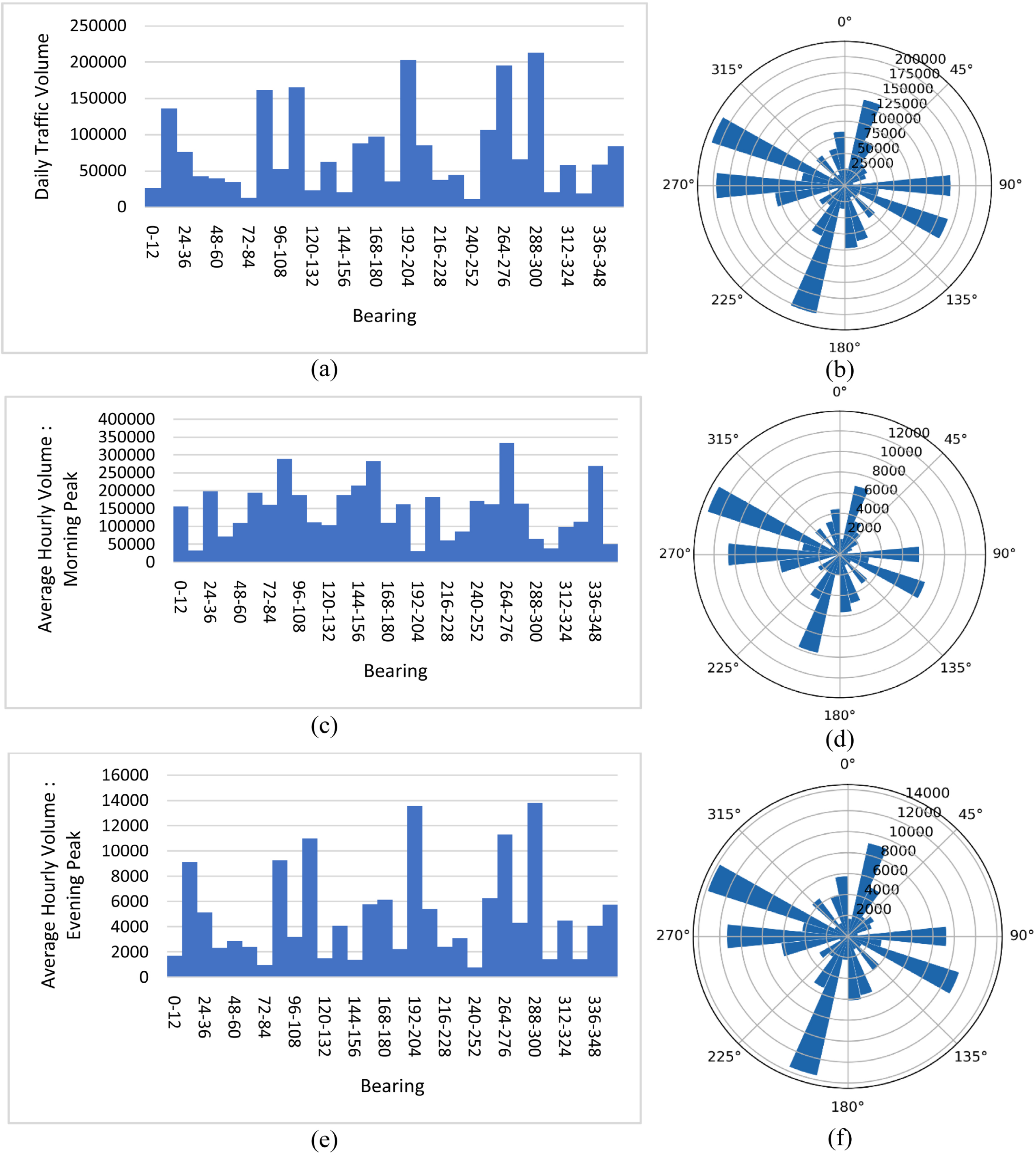

Figure 12. Traffic flow orientation: Daily traffic ((a), (b)), Average hourly morning peak ((c), (d)) & Average hourly evening peak ((e), (f)) of the Bronx.

SSE opposite scenario occurs. In other directions, the mismatches are not much significant.

4. Discussion

The presented visualizations herein provide several insights that can help better

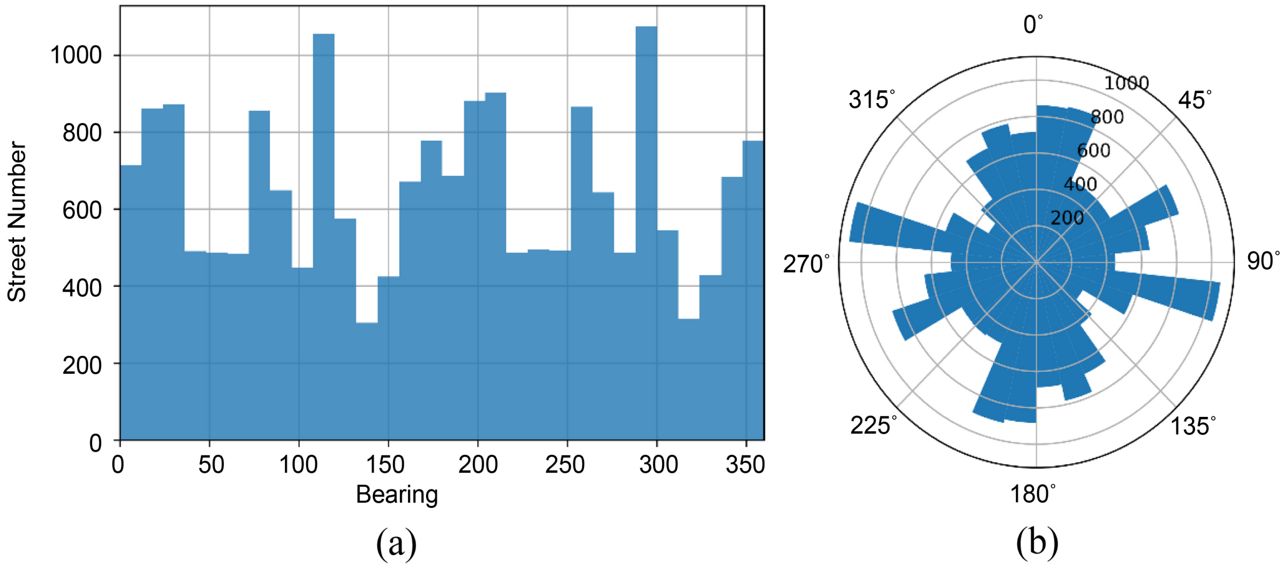

Figure 13. Street network orientation of the Bronx ((a), (b)).

understand network-wide travel behavior as compared to the built street network topology. This study successfully draws our attention to the existence of considerable discrepancies between the travel pattern of city residents and the orientation of the street network over a city. For instance, the results showed that both the Bronx and Staten Island boroughs have street networks that are oriented in all directions with very few clear clusters of streets oriented in certain directions. However, the traffic was mainly on the streets in the ESE, SSW, WNW, E, and W directions for the Bronx borough, and in the E, W, and EbS directions for Staten Island. These measures provide a clear overview of whether there is a match between the built street network and where people travel in a city. Table 6 provides a comparative summary of the street orientation and travel demand of the four boroughs.

As an example, Calhoun Avenue is in a dense cluster of streets in the Bronx oriented in the NNW direction. From our raw dataset, we see that street, like many in the same orientation, has a total daily traffic flow of 229 vehicles. When zooming in to its location, it turns out that this street is one way with high on-street parking activity in a residential area. These characteristics are core reasons why that street and many in the same cluster do not experience high demands, hence a mismatch is created between the orientation of the street network and the orientation of trips. A different example from Queens is Rockaway Boulevard, which is oriented in the E-W direction where not many streets share the same orientation. However, when looking at the traffic flow, that street had daily traffic of 7454 vehicles in the E direction and 10,426 in the W direction. That road is a major four-lane two-way street with many small businesses, which explains the relatively high demand compared to Calhoun Avenue in the Bronx.

While this study expresses the aforementioned discrepancies, it also provides important insight into the usability of city-wide street networks as they can show

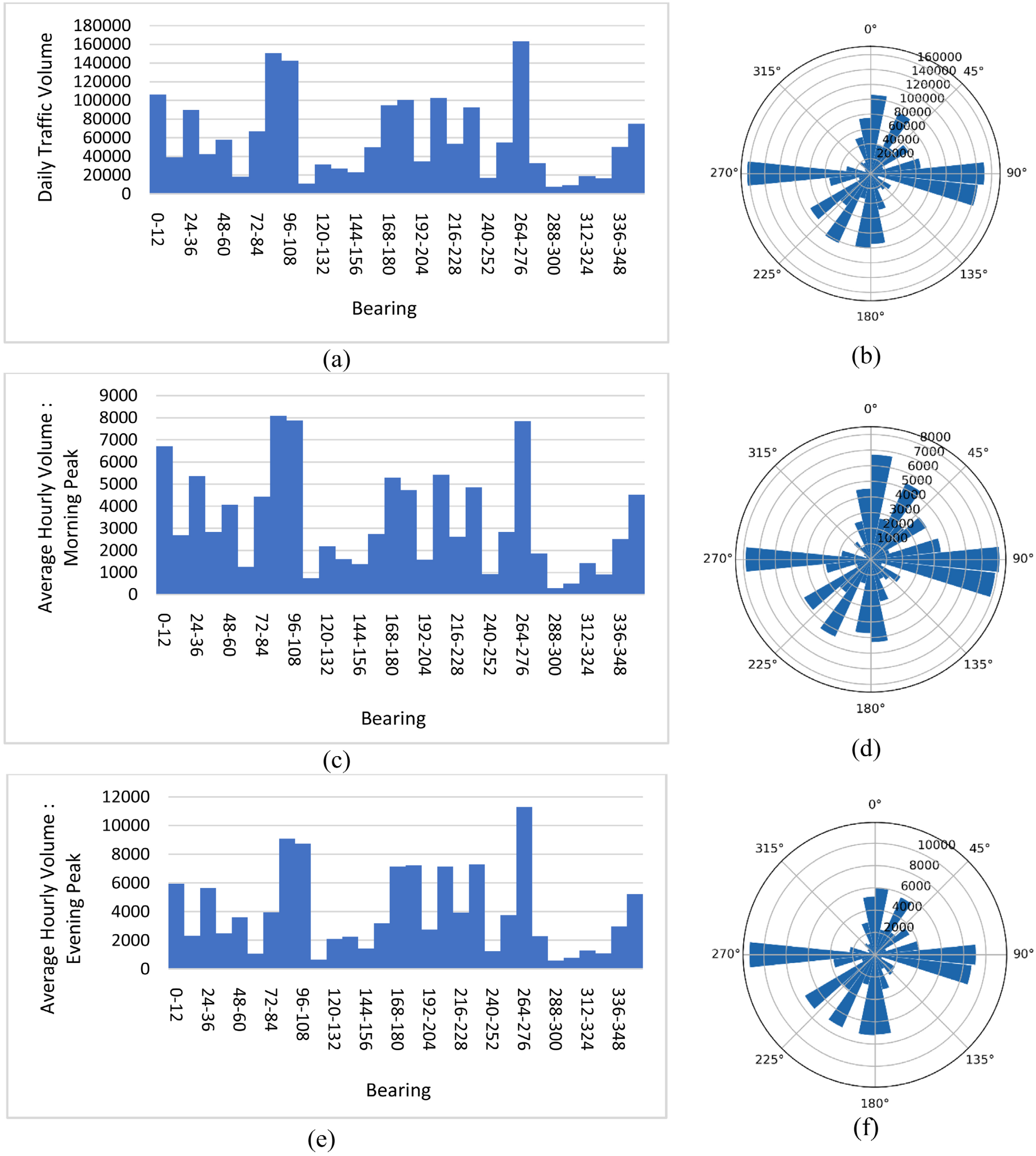

Figure 14. Traffic flow orientation: Daily traffic ((a), (b)), Average hourly morning peak ((c), (d)) & Average hourly evening peak ((e), (f)) of Staten Island.

clearly what roads are being used the most based on their orientation. For example, on 240˚ - 252˚ of Queens, 36˚ - 48˚ of Brooklyn, 348˚ - 360˚ of the Bronx, 300˚ - 312˚ of Staten Island contain a significant number of roads in comparison to the trips are made in those directions. This is evident that streets in those directions have less usability which could help in identifying alternative routes to

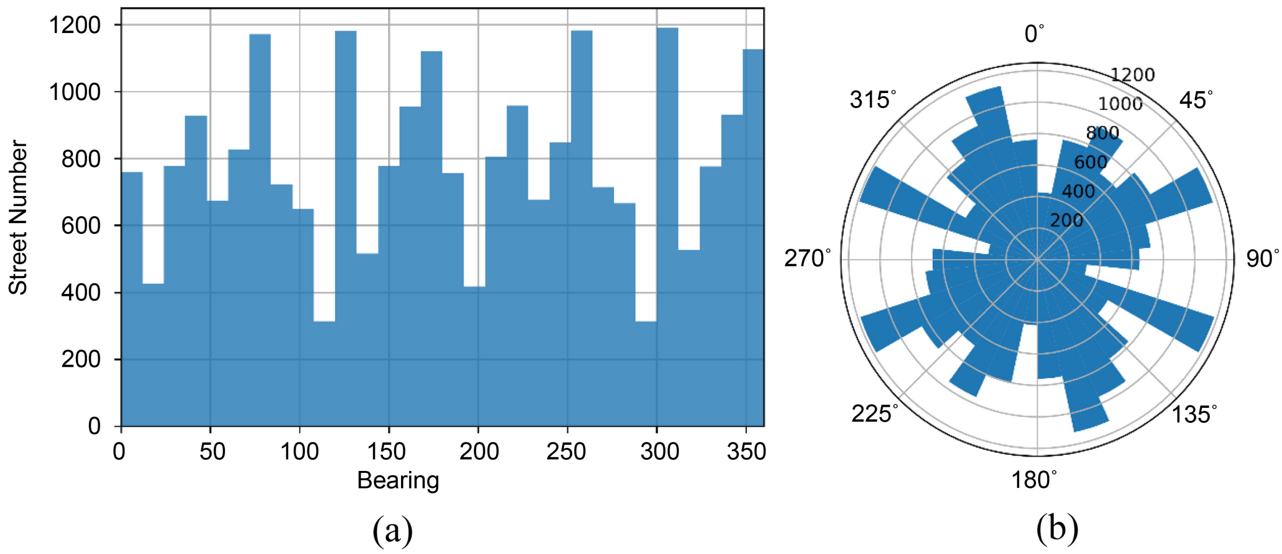

Figure 15. Street network orientation of Staten Island ((a), (b)).

Table 6. Comparative zonal trip and street distribution of four NYC Boroughs.

Boroughs	Zone (Dense Clusters of Built Streets)	Zone (High Flows)	Zone (Higher Roads, Lower Flows)	Zone (Higher Flows, Fewer Roads)
Queens	NNW, ENE, SSE, WSW	NE to SE, NNW, E-W line, WNW	SWbW, NEbE	E, ESE
Brooklyn	WNW, ENE, WSW	NbW, WSW, SbW, ENE	NNW, SSW	NNW, SSE
The Bronx	Uniform	ESE, SSW, WNW, E-W line	ENE, WSW	W
Staten Island	Uniform	The region between North to East, South-West	Region between North-West. South to East	E-W line

redistribute traffic evenly (considering mobility measures) and efficiently manage traffic over entire networks. Reverse discrepancies of fewer streets with a high flow are also observed (*i.e.*, 84˚ - 96˚ of Queens, 144˚ - 156˚ of Brooklyn) which shows how many streets remain unused creating an imbalance in the network usability. The visualizations also show the travel trend of people during rush hours. Though the AM and PM peaks look similar in the analysis, close attention reveals the domination of PM peak over AM peak. Though this study provides important insights into travel behavior and how road network is used, it has some limitations. The road capacity, lane count, and road categorization (arterial, collector, local, etc.), some of the important metrics to define the motivations for travel behavior along NYC, were not well examined. These essential components will be included in future research directions to connect mobility and usability as a whole. Nevertheless, the visualization methodology clearly paves the way for understanding how people travel over the network and which roads are being used most according to their orientation with respect to street networks. This can come helpful in making decisions to prioritize specific street corridors that experience significant trips and proper traffic monitoring methods can be implemented based on it.

5. Conclusions

This study introduces a novel methodology to visualize city-wide travel patterns. The methodology is based on the work done by Boeing to visualize street network orientations. Our main objectives are to develop 1) a way to visualize where people travel the most over a city street network and 2) evaluate city street network usability considering the discrepancies between network order and travel orientation. The study reveals important insights into how people travel in urban street networks. In general, three core factors define where people travel in a network: accessibility to land use, attractiveness of land use, and mobility of roads. When land use is highly attractive or has a high demand (e.g., a busy workplace, an attractive recreational area, etc.), such land-use attracts many trips from various directions (depending on where people live or where they come from) [19]. These trips are then assigned to roads based on mobility measures of such roads (defined by travel speed, congestion levels, resistance measures such as traffic signals, etc.) and accessibility to the destination (some roads may provide higher accessibility to the land use compared to others). Hence, when looking back at the discussion of the Bronx and Staten Island, conclusions could be drawn based on the comparison between the orientation of the street network and the travel patterns based on the three aforementioned factors. For instance, the mismatch between how the street network is built and where traffic exists could indicate that maybe some roads have higher mobility than others due to high demand for on-street parking thus reducing mobility, the existence of many traffic signals which may cause high delays, or existence of dense clusters of attractive land uses in certain areas compared to other areas. Future study will address these mismatches and explain them based on classification of those streets (*i.e.*, Arterial, Local, etc.), roadway capacities, accessibility, and mobility comparison of streets with their respective traffic flows. With further investigation into these measures, policymakers would be able to identify what countermeasures could be needed to create a balance between the built-in network and traffic demands. Such a balance is needed to create a more livable environment, a highly mobile network, and more efficient policies.

The developed visualizations prove useful in monitoring traffic over an entire network for various applications. For instance, through monitoring such visualizations, routing recommendations could be made when needed to mitigate congestion from a set of streets that are highly used to less-used streets to create a balance and distribute congestion somewhat homogeneously throughout a network. Developing measures on the usability of multimodal networks by creating separate visualization for bike lanes vs. bicycle traffic, transit routes vs. transit ridership, as well as city streets vs. vehicular traffic will greatly help the respective transportation authorities to identify sustainable solutions for livable and smart cities. These visualizations could prove highly effective in monitoring multimodal travel patterns and making informed decisions to improve the efficiency of the city network. Future research will investigate these applications using more comprehensive data from various cities to prove the generalizability of the approach.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: O. A. Osman; data collection: J. Palit and A. O. Osman; analysis and interpretation of results: O. A. Osman, J. Palit, and H. Rakha; draft manuscript preparation: J. Palit, O. A. Osman, and H. Rakha. All authors reviewed the results and approved the final version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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