Improving Network Travel Time Reliability Estimation with Network Partitioning

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ABSTRACT

Network travel time reliability can be represented by a relationship between network space-mean travel time and the standard deviation of network travel time. The primary objective of this paper is to improve estimation of the network travel time reliability with network partitioning. We partition a heterogeneous large-scale network into homogeneous clusters with well-defined Network Fundamental Diagrams (NFD) using directional and non-directional clustering methods. The impacts of the partitioning approaches, as well as the number of clusters, on the network travel time reliability relationship are explored. To estimate individual vehicle travel times, we use two distinct approaches to allocate vehicle trajectories to different time intervals, namely full trajectory and sub-trajectory approaches. We apply the proposed framework to a large-scale network of Chicago using a 24-hour dynamic traffic simulation. Partitioning and travel time reliability estimation are conducted for both morning and afternoon peak periods to demonstrate the impacts of travel demand pattern variations. The numerical results show that the sub-trajectory method for the travel time reliability estimation and the directional partitioning with three clusters have the highest performance among other tested methods. The analyses also demonstrate that partitioning a heterogeneous network into homogeneous clusters could improve network travel reliability estimation by assigning a separate relationship to each cluster. Also, comparing morning and afternoon peak periods suggests that the estimated parameter for the linear network travel time reliability relationship is dependent on the coefficient of variation of density.

Keywords: *Network Fundamental Diagram (NFD), Reliability, Travel Time Distribution, Heterogeneous Network, Clustering, Density Distributio***n**

INTRODUCTION

Simulation-based and empirical studies in the literature confirm the existence of a consistent and well-defined network wide relationship between flow and density known as Network Fundamental Diagram (NFD) , also known as Macroscopic Fundamental Diagram (MFD) in other studies (*1*-*5*). The heterogeneous spatiotemporal distribution of congestion across real networks often creates scatter and hysteresis in the NFD (*6*). Partitioning the heterogeneous network into homogeneous clusters based on the spatial and temporal distribution of link densities is expected to improve estimation of well-defined NFDs. On the other hand, the degree of uncertainty due to the variability of travel time and the behavioral characteristics of travelers is also a contributing factor in the network performance evaluation. In the literature, the distance-weighted standard deviation of travel time rate is considered as a measure of travel time variability (*7*), and is to have an approximately linear relationship with the mean travel time rate (*8*). In this paper, we explore how network partitioning can improve estimation of the network travel time reliability.

Previous studies have mostly used microscopic simulation models (*9*, *12, 13*), empirical data (*6*, *10*, *12*), and simulation-based dynamic traffic assignment (*11*) to study the factors affecting the shape and scatter in the NFD. Few studies have also explored the network travel time reliability in connection with NFD to further capture network dynamics and day-to-day variations in network traffic (8, *14-19*). More specifically, Gayah et al. (*20*) proposed an analytical model representing the day-to-day variability of travel time in a network. Boyacı and Geroliminis (*21*) characterized the NFD for a network with variable link lengths and signal specifications, including variations caused by turning movements and heterogeneous drivers. Kwon et al. (*22*) developed a linear regression and tree-based procedure to capture the day-to-day diversity of travel time. Noland and Polak (*23*) reviewed both the theory and empirical results of several past studies that evaluated the travel time variability.

Congestion naturally imposes heterogeneity to a network. Previous studies (*24*-*26*) explored the properties of NFD in a heterogeneous network and suggested approaches to cluster the network in regions with more homogeneity in the spatial distribution of congestion and less scatter in the estimated NFDs. Along this line, Briganti et al. (*27*) clustered a heterogeneous transportation network based on the spatial distribution of urban activities and consequently estimated NFDs for partitioned sub-networks. In another study, Huang and Gao (*28*) reviewed existing heterogeneous network partitioning algorithms and evaluated different methodological approaches. Characterizing NFD and its connection with variability of travel time can be utilized to develop more efficient routing strategies (*27*) and urban planning activities (*29*). Considering the application of heterogeneous network partitioning in traffic control strategies (see for example *42*, *43*), we intend to explore impacts of the network clustering on travel time reliability measures.

In this paper, we incorporate different network partitioning and travel time reliability estimation approaches in a large-scale network of Chicago using a 24-hour dynamic traffic simulation model. We show that the network travel time reliability relationship depends on the coefficient of variation of density calculated over the simulation horizon and across the links in each cluster, which itself relates to the network partitioning based on the density variations. The paper also demonstrate an application of partitioning on an actual large scale network, exploring the impacts of different congestion patterns in the morning and afternoon peak periods and comparing two partitioning approaches (directional vs. non-directional), and two methodologies for the network travel time reliability estimation.

The remainder of the paper is organized as follows. The paper continues with an overview of NFD, travel time reliability measure estimation, and network partitioning followed by a description of the proposed methodologies. The next section discusses the study area and specifications of the case study network and identified clusters. We then employ a 24-hour dynamic traffic simulation model to partition the full network, deriving NFDs and the network travel time reliability measures for the full network and all the identified sub-networks. Finally, conclusions and remarks on possible directions for future research are presented.

BACKGROUND

In this study, we investigate two main themes. First, how the spatial distribution of congestion affects the shape and scatter NFD and second, deriving a robust relationship for travel time reliability analysis. We first discuss the recent developments in the literature related to NFD, network partitioning, and travel time reliability measure estimation.

To estimate NFD (*31*-*36*), network wide average flow and density are often calculated as follows (*3*, *30*):

$$Q = \frac{\sum_i^M l_i q_i}{\sum_i^M l_i} \tag{1}$$

$$K = \frac{\sum_i^M l_i k_i}{\sum_i^M l_i} \tag{2}$$

where

Q: distance-weighted average of flow;
K: distance-weighted average of density;
q_i: individual link average flow;
k_i: individual link average density;
l_i: lane-length i, $i = 1. \dots . M$; and
M: total number of links.

The general formulation of a clustering problem for a pre-specified number of clusters (N_c) is presented here. Each cluster contains a connected set of links with similar level of congestion, where connectivity is explicitly imposed by a set of constraints as introduced in (*37*). Connectivity is defined using the concept of directed acyclic graph. Here, we introduce a modified objective function, which needs a smaller number of variables and is tractable for networks with larger sizes. The new objective function estimates the summation of weighted variances (TV) in different clusters defined as follows:

$$\sum_{i=1}^{N_c} \sum_{j \in C_i} \left(d_j - \bar{\mu_i}\right)^2 = \sum_{i=1}^{N_c} \sum_{j=1}^{N} x_{ij} \times \left(d_j - \bar{\mu_i}\right)^2 \tag{3}$$

where d_j is the measured data (density) for link j and $\bar{\mu}_i$ is the estimated average for cluster i. x_{ij} is a binary variable indicating if link j belongs to cluster i or not. The average value of each cluster depends on the clustering assignment and is not defined in advance. Hence, the algorithm starts from a random guess for $\bar{\mu}_i$s and solves a Mixed Integer Linear Program (MILP) to find the best clustering assignment for the current set of $\bar{\mu}_i$. Then, the $\bar{\mu}_i$ variables are updated by taking the real average values of clusters. The value of objective function decreases at both optimization and updating steps. These procedures continue until the convergence of the objective function. This approach follows a similar variables concept of K-means algorithm to find the best clusters. As the solution depends on the starting point, we run the algorithm several times with different initial points to get the best one. The mathematical formulation is considered beyond the scope of this work and is omitted due to size limit.

The distance-weighted standard deviation of travel time per unit of distance is often used as a measure of travel time variability. Network travel time reliability can be characterized by a travel time distribution, which contains two key parameters of mean and standard deviation. The first component describes the central tendency and the second shows the dispersion. To discard the impacts of trip distance variations on travel time reliability, the travel time (*t*) needs to be normalized by trip distance (*d*). So, the travel time per unit distance (*t′=t/d*) is considered as the travel time measure (*12*). Thus, the distance-weighted mean and standard deviation of travel time rate can be estimated as follows:

$$\mu = \frac{\sum_{i=1}^{M} d_i t'_i}{\sum_{i=1}^{M} d_i} = \frac{\sum_{i=1}^{M} t_i}{\sum_{i=1}^{M} d_i} \tag{4}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{M} d_i (t'_i - \mu)^2}{\sum_{i=1}^{M} d_i}} \tag{5}$$

To construct the relationship between distance-weighted mean and standard deviation of travel time rate, a linear model has been suggested in the literature (*38-40*):

$$\sigma(t') = p_1 + p_2 \mu(t') \tag{6}$$

where

$\sigma(t')$: standard deviation of t',
$\mu(t')$: mean value of t', and
$p_1 . p_2$: coefficients

The paper uses simulation-generated vehicle trajectories of a network to explore this relationship for each identified cluster in the network. To obtain the distribution of travel time per unit of distance in the network, we propose two approaches:

Trajectory Approach: This approach requires the following steps to specify the relationship between μ and σ:

1. Extract the travel time and travel distance for each set of consecutive links that is traveled by a certain vehicle. The set is the longest consecutive sub-set of the vehicle trajectory links that

includes links belonging to the same sub-network. The entry time to the first link of the set determines the time interval that the set belongs to as an observation. The observations from different pieces of vehicle trajectories associated with each sub-network and time interval are used to compute the mean and standard deviation of travel times per unit of distance. Each observation has two components: a travel time, which is the total elapsed time by vehicle i at set j, and a travel distance, which is the total length of links belonging to set j.

2. Calculate the distance-weighted mean and standard deviation of travel times per unit of distance for each time interval in each sub-network (Equations 4, and 5). Each time interval in each sub-network produces a sample point to be used in the next step.
3. Draw the standard deviation of travel time per unit of distance versus its mean value for each sub-network and estimate the coefficients (Equation 6).

The same process is conducted to specify the travel time distribution measures for the study area network (union of all clusters). However, in this case each vehicle trajectory is considered as one set that belongs to the time interval associated with the vehicle departure time.

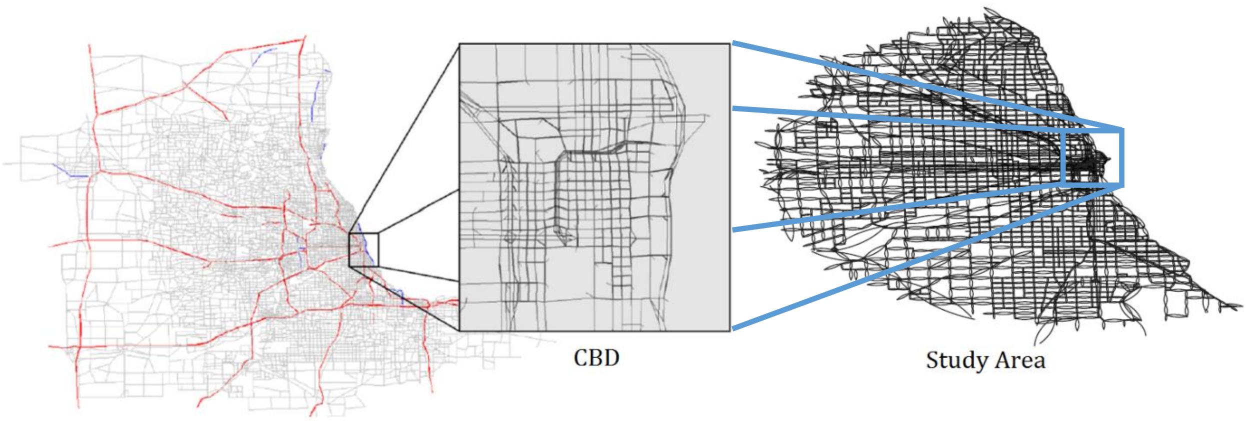
Sub-Trajectory Approach: This approach also requires three steps to specify the relationship between μ and σ. The second and third steps are exactly the same as step 2 and 3 of the trajectory approach. However, step 1 is modified as follows:

1. Extract the travel time and travel distance for each segment. A segment is a piece or entire of a trajectory produced by a vehicle traveling in a sub-network during a certain time interval. Each segment is considered as one observation for the associated sub-network and time interval to be used for mean and standard deviation calculations. In this approach, the entire segment is traveled during the associated time interval and the maximum travel time is equal to the time interval length. This is unlike the Trajectory approach, in which each set is assigned to a time interval solely based on the departure time.

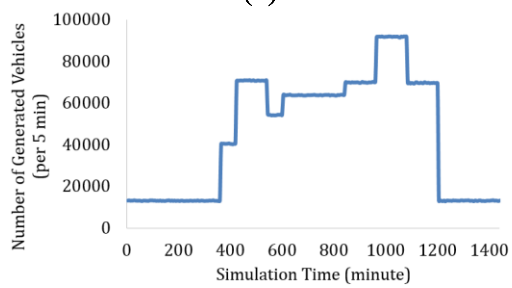
The same process is conducted to specify the travel time distribution measures for the study area network. However, in this case, as the vehicles do not travel in different clusters, their trajectories over each time interval is not separated into multiple segments.

DATA DESCRIPTION AND STUDY AREA

The Regional Chicago network is considered for the case study (see Figure 1(a)). This network contains 40,443 links, 13,093 nodes, and 1,961 traffic analysis zones. Traffic data are simulated using DYNASMART. Figure 1(b) illustrates the hourly network loading profile over the 24-hour simulation horizon. The data for the demand and network are obtained from Chicago Metropolitan Agency for Planning (CMAP). A subset of 9,915 links around the CBD area is selected for partitioning based on link density variations over time and space. This subset forms the study area network depicted in Figure 1(a). 5-minute time intervals are considered in order to analyze the network characteristics including NFD, reliability measure estimation, and network partitioning. Figure 2 illustrates the entire day NFD and travel time reliability statistics calculated by both trajectory and sub-trajectory approaches. Network wide average flow, average density, and weighted average mean/standard deviation of travel times per unit of distance are calculated for each 5-minute time interval resulting in 288 sample points on each graph. Morning peak, evening peak, and off-peak periods are separated by different colors to provide a better interpretation of the simulation results.



(a)



(b)

FIGURE 1 (a) Schematic sketch of the Chicago metropolitan network, Chicago CBD and the study area network including 9,915 links; (b) Chicago metropolitan network 24-hour loading profile

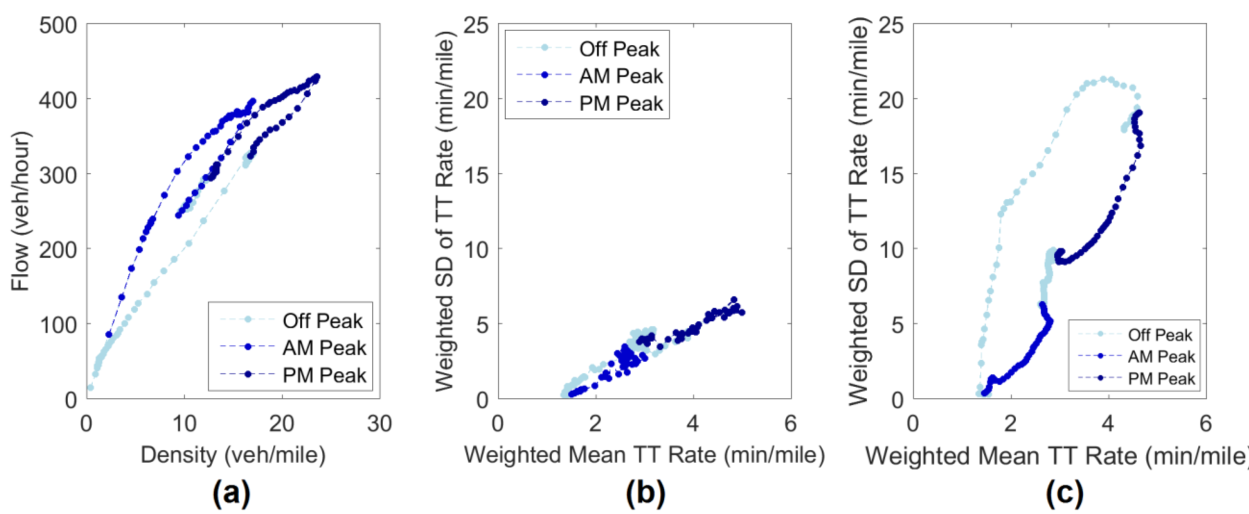


FIGURE 2 (a) NFD, (b) Reliability graph estimated by the trajectory approach, and (c) Reliability graph estimated by the sub-trajectory approach for the study area network over the 24-hour simulation horizon

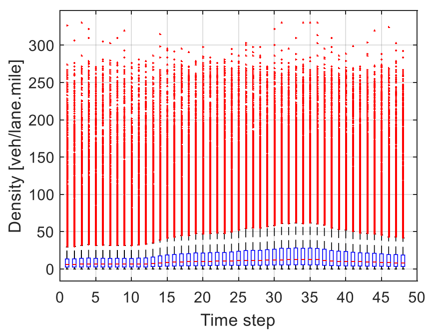
In Figure 2, the flow-density NFD is plotted (Fig. 2a), while the standard deviation vs. mean of travel time rate with the trajectory and subtrajectory approach is shown as well (Fig. 2b and 2c respectively). Note that the evening peak reflects grater values compared to the morning peak for both average flow and density in the NFD. The NFD follows a smooth trend as it reaches the maximum AM peak flow around 9:00 AM. Afterwards, the network is unloading and the system begins to recover while there is a decrease in average flows. As the demand level increases at mid-day, the system becomes congested again, and density increases. When the average flow reaches the maximum value at the PM peak (around 6:00 PM), the average density reaches the highest point, and the network experiences the highest possible congestion. Then, the network is unloading again and begin to recover until it returns to a stable condition. An incomplete hysteresis loop is formed during the AM peak period followed by a complete hysteresis loop during the PM peak period.

In the trajectory approach, the reliability measure (slope of the estimated linear relation) is almost the same for AM and PM peak periods, and significant fluctuations can be observed. This is not the case for the sub-trajectory approach. The observed value range of mean travel time are exactly the same for the two methods, but the sub-trajectory approach estimates larger values for the standard deviation of travel time per unit of distance compared to the trajectory approach. There are fewer fluctuations in the sub-trajectory approach since each travel time segment occurs at the same time interval. However, in the trajectory approach, different sets of a certain time interval might occur at different simulation time intervals as they only share the same departure time. The trajectory approach has a lower standard deviation as it ignores the variation of travel time over each vehicle trajectory by simply assuming that the travel time is uniformly distributed over the traveled distance (which might occur in multiple time intervals). However, in the sub-trajectory approach, each vehicle trajectory is divided into multiple segments and as a result better captures the variation of travel time over the traveled distance.

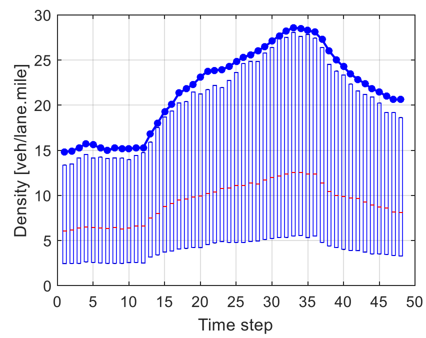
A four hour AM-Peak (from 6:00 AM to 10:00 AM) and a four hour PM-Peak (from 3:00 PM to 7:00 PM) are considered in order to perform detailed analyses for different clustering approaches in the next two sections. Note that each of these periods includes the peak hours and pre- and post-peak hours to demonstrate the network traffic flow dynamics.

CLUSTERING THE HETEROGENEOUS NETWORK

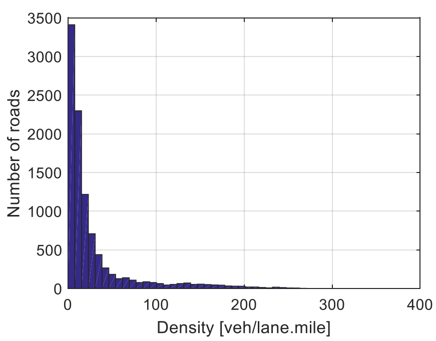
In this section, we elaborate on the propagation and distribution of congestion in the study area network during the morning and evening peak periods. The density of different links measured every 5 minutes is utilized as an indicator representing the level of congestion. First, a detailed analysis is performed to find a proper configuration to run the clustering algorithm. As the analysis approach is identical for both the morning and evening peak, here we explain only the evening peak data analysis. Figure 3(a) depicts a box-plot representation of density at different time intervals during the evening peak. As seen in the zoomed Figure 3(b), the average and standard deviation of density increase over time. Average and median values are depicted using blue and red colors respectively. We select time interval (t=33) for both morning and evening peaks, where the average and standard deviation of density are at a very high level. This time represents a condition where the network is heterogeneously congested. The histogram of densities at t=33 (Figure 3(c)), shows that the density holds a bi-modal distribution (i.e. many roads have a small density and some roads have a very high density), which is the reason for existence of many outliers in the box-plot representation. The study area network contains many bi-directional roads (4307 pairs). To investigate the existence of directional congestion, we plot the histogram of standard deviation in bi-directional roads in Figure 3(d). According to this figure, most of the bi-directional roads have a smaller standard deviation than the average standard deviation in the network. Hence, it is not expected to have many bi-directional roads appearing in different clusters.



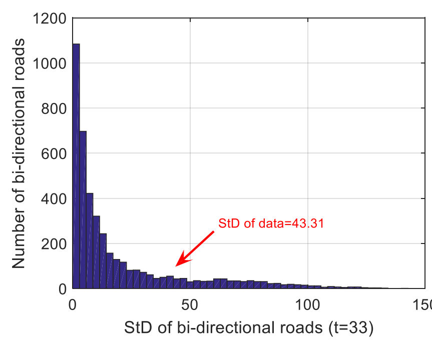
(a) Box-plot representation of roads density



(b) Average, median, and quantiles



(c) Histogram of densities at t=33



(d) Histogram of densities in bi-directional roads at t=33

FIGURE 3 Density temporal and spatial distributions for the PM peak period

In this part, the methodological framework utilized to partition the study area network is discussed. Since the size of the study area network is very large (about 10,000 links), applying the exact formulation (explained earlier) is computationally not practical. Hence, a few simplification steps are introduced to improve computational efficiency, by finding and grouping the nearby roads with similar level of congestion throughout the network. Then, a set of homogeneous and non-overlapping groups, named local "homogeneous components", are chosen among them. Finally, the exact formulation can be applied to the reduced size network including obtained components and remaining individual roads. In the following, different simplification steps are explained in details.

In the first step, by comparing the standard deviation of density data in the entire network with histogram of density in bi-directional roads, we can define a certain threshold under which the directional heterogeneity can be ignored. In other words, bi-directional roads with lower standard deviation of density (density difference between two directions) can be grouped together and considered as one element. The selected value for this threshold is 18 veh/mile, which is about one-third of the standard deviation of the entire data. Considering such thresholds or not is the main factor in specifying directional or non-directional partitioning approaches.

The next step finds a set of similar links around each link (up to a certain distance) in the network. We have utilized the “Snake” methodology introduced in (*26*). This method iteratively obtains the most homogeneous neighboring road around the set and adds it to the current set. Snakes grow up to a certain size (100 in this study) independently, where connectivity is guaranteed by construction in this method. Then the most homogeneous non-overlapping components are extracted with a greedy approach from the set of components obtained by the snake methodology. First the most homogeneous snake is selected. Then, at each step, the most non-overlapping homogeneous component with the previous selected components is selected. This procedure continues until no non-overlapping component exists. At this stage, groups of homogeneous links and single non-assigned links can be partitioned using the exact formulation with a feasible computational efficiency.

The performance of the proposed methodology is examined for the study area network using directional and non-directional approaches for different number of clusters ranging between 2 and 4. As an example, the result of partitioning into three clusters with non-directional approach at morning peak period is depicted in Figure 4(a). A well-established metric called total variance, TV_N, is utilized to evaluate the efficiency of the clustering algorithm. This metric is defined as the ratio between weighted variance of density in partitioned case to un-partitioned case:

$$TV_N = \frac{\sum_{i=1}^{N_c} N_i \times \mathrm{var}(C_i)}{N \times \mathrm{var}(C)} \tag{7}$$

where N_i denotes number of links in cluster i and $C = \bigcup_{i=1}^{N_c} C_i$. The value of TV_N is demonstrated at different time intervals in Figure 4(b). The red curve represents the efficiency of obtained clusters for the speed data and the blue curve represents the density-based measure. TV_N takes its smallest value during time interval 33, when clustering is performed. Another interesting observation is that the partitioning has a higher quality around time interval 33, which confirms the spatial and temporal correlation of congestion distribution. A similar pattern is observed for both speed and density data; however, the blue curve has a lower TV_N value since the density data is utilized as an input for clustering. Figure 4(c) and Figure 4(d) present the same results as for directional partitioning with 3 clusters at the evening peak period.

A detailed comparison of the minimum and average values of TV_N over the AM and PM peak periods for different clustering approaches is illustrated in Figure 5. Results confirm superiority of the directional partitioning. Also, partitioning into 3 clusters instead of 2 clusters improves the quality of the partitioning. However, increasing the number of clusters to 4 does not significantly improve the partitioning quality as compared to the 3-cluster case. Furthermore, partitioning is more important for the PM peak period where there is greater heterogeneity over the simulation horizon. Therefore, directional partitioning into 3 clusters for the PM peak period is considered for detailed analyses of NFD and travel time reliability measures in the next sections.

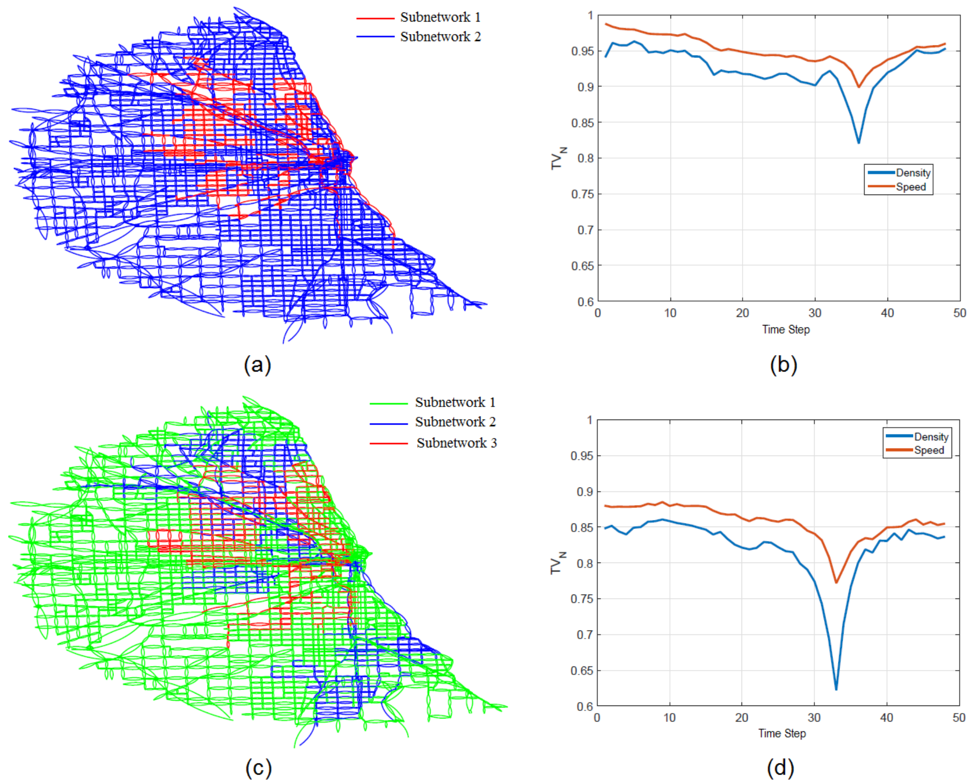


FIGURE 4 Partitioning results (a) 2 clusters for AM peak and non-directional approach, (c) 3 clusters for PM peak and directional approach, (b) Speed and density descriptor of clustering quality during the AM peak, and (d) Speed and density descriptor of clustering quality during the PM peak

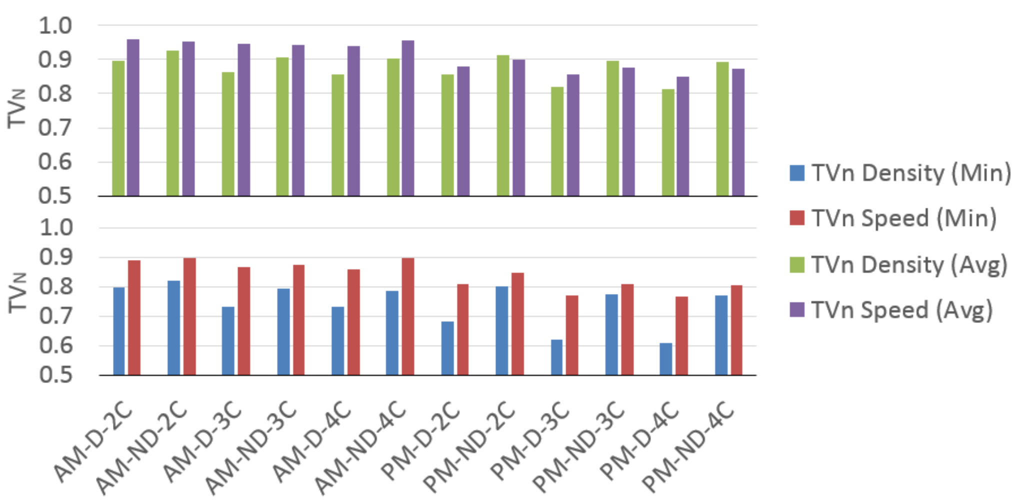


FIGURE 5 Minimum (lower graph) and average (upper graph) values of TV_N over the simulation horizon (AM and PM peak periods) for different clustering approaches with 2, 3, and 4 clusters

NFD AND RELIABILITY MEASURE ESTIMATION

Average flow and density at each 5-minute interval during the AM and PM peak periods are calculated using analyses of simulated vehicle trajectories for different clustering approaches. The trajectories are divided into segments based on the link assignment to each cluster. The relationship between average flow and density over different 5-minute time intervals is considered as the NFD for each cluster. In each cluster, the AM or PM peak NFD has a smooth pattern in which average flow and density grow at the same time until a maximum flow rate is observed in the first phase. After this phase, the flow decreases while the density increases, resulting in an excess congestion and generation of a hysteresis loop. Finally, at the end of the loading phase, average flow and density are decreased in the last phase. Depending on the congestion level, the hysteresis loop size varies and the second phase might not even exist.

Figure 6 shows NFDs, and mean versus standard deviation of travel times per unit of distance (by both the trajectory and sub-trajectory approaches) for the study area network and its 3 clusters. The directional partitioning method is used for the evening peak period. The average density in the study area network is 11.5 veh/mile. The ordered pair of size (number of links) and average density (veh/mile) for these three clusters are (6282, 6.7), (3274, 17.4), and (359, 40.3), respectively.

Figure 6(a)-6(d) show that clusters reflect different NFDs in terms of the shape, maximum and average density and flow, and the area of the hysteresis loop. This emphasizes one of the main contributions of the clustering approach, which states that a single NFD for the entire network cannot properly describe the network performance because in most cases, congestion is heterogeneously distributed throughout the network. It can be observed that the maximum flow and the area of the hysteresis loops are increased by the increase in the cluster average density.

In Figure 6(e)-6(h), upper and lower diagrams are estimated by the trajectory and sub-trajectory approaches, respectively. The mean travel time per unit of distance range is exactly the same in both approaches for all sub-networks and the study area network. However, this is not the case for the standard deviation of travel time per unit of distance. In the study area network there is a significant difference in the range of standard deviation of travel time per unit of distance between the two approaches, since the sub-trajectory method captures the variation of travel time along each vehicle trajectory, resulting in greater overall variability across sub-trajectories than across full trajectories. However, within clusters, these ranges are comparable for both methods, which is due to increased homogeneity of congestion distribution.

Detailed descriptors of the reliability diagrams besides the calibration results for the linear model are given in Table 1. This table presents the average of the mean and standard deviation of travel time rate, point estimates of the model coefficients, t-statistic, associated p-value, and adjusted R-squared values with 95% confidence bounds. The results illustrates that all coefficients are statistically significant for the linear model in both approaches. The adjusted R-squared values are generally high, which indicates an acceptable fit. However, the overall R-squared values estimated by the sub-trajectory approach are higher. The loading and unloading phases follow different paths in the reliability diagrams, although in many cases, the relation between mean and variability of travel time is still linear.

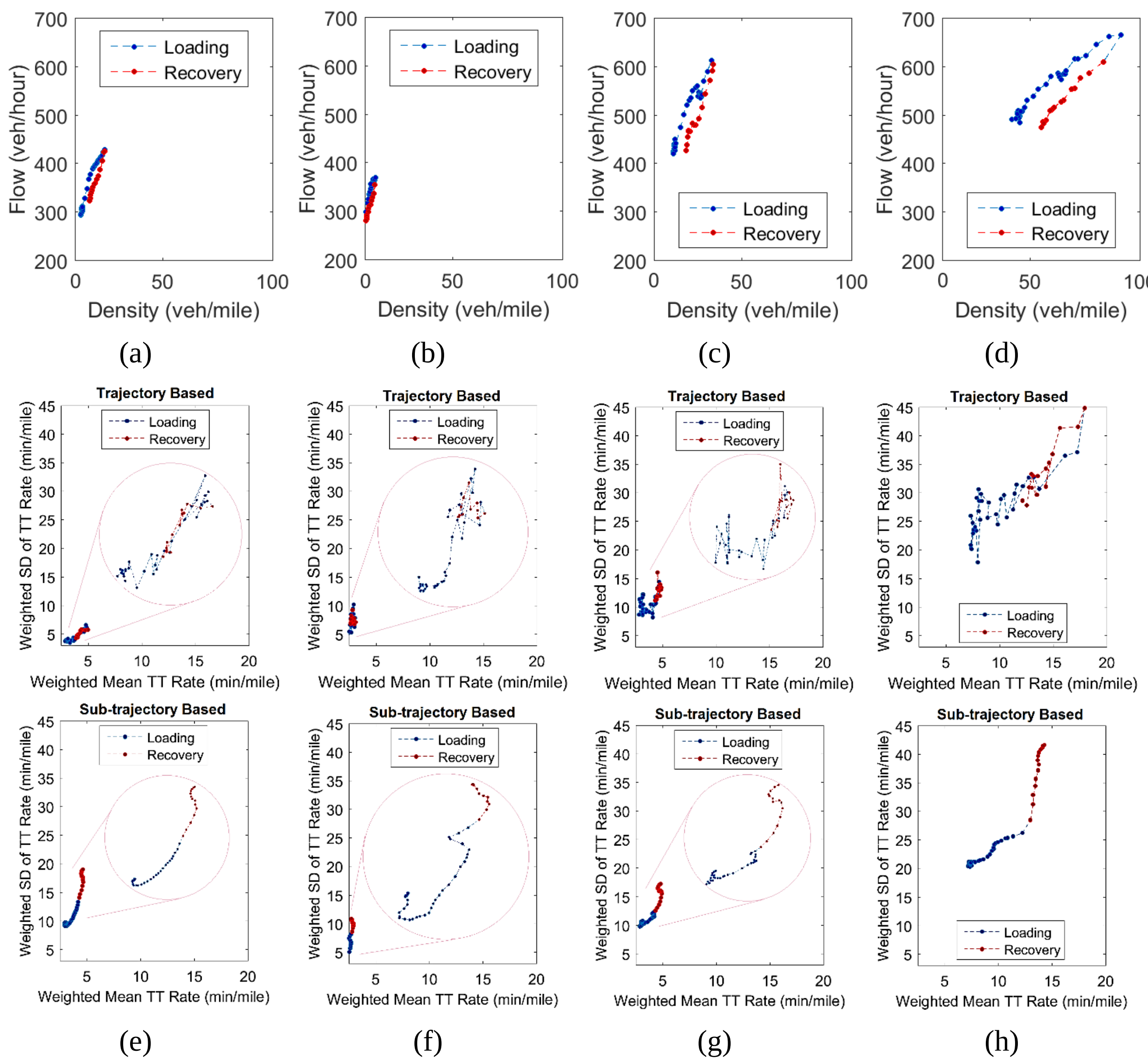


FIGURE 6 NFDs over the PM peak period for the directional partitioning approach for (a) study area network; (b) cluster 1 with 6.7 veh/mile average density; (c) cluster 2 with 17.4 veh/mile average density; (d) cluster 3 with 40.3 veh/mile average density; and associated travel time reliability diagrams for Trajectory and Sub-Trajectory approaches in (e) study area network; (f) cluster 1; (g) cluster 2; and (h) cluster 3

TABLE 1 Estimation of the Reliability Coefficient For PM-Peak Directional Partitioning

Reliability: Trajectory Approach		
	Linear Model Coefficient	Adjusted

Network / Subnetwork	Size (Links)	Linear Model Constant (p_1)	p_2	t-stat	p-val.	R^2
Network	9915	0.10	1.19	17.3	<0.00001	0.864
Subnetwork 1	6825	-11.1	6.54	12.8	<0.00001	0.775
Subnetwork 2	1922	3.77	1.89	6.77	<0.00001	0.489
Subnetwork 3	1168	12.1	1.57	12.3	<0.00001	0.761
Reliability: Sub-trajectory Approach						
Network	9915	-5.77	4.87	15.7	<0.00001	0.840
Subnetwork 1	6825	-13.9	8.16	13.5	<0.00001	0.795
Subnetwork 2	1922	0.77	2.99	12.3	<0.00001	0.762
Subnetwork 3	1168	-0.18	2.68	19.1	<0.00001	0.886

Overall, the two methods estimate different values for the reliability measures. The Sub-Trajectory approach, which estimates larger coefficient of reliability, is preferred to the other approach. First, in this method, considering the travel information during each time step (5 minutes) reflects a more detailed description of travel time reliability than only focusing on the departure time interval. Second, results of the Sub-Trajectory approach indicate a smooth change of mean and standard deviation of travel time rate during the simulation time, while for the Trajectory approach considerable fluctuations is observed. This is due to combining travel time information of trajectories that share the same departure time but might take place over different time intervals. Therefore, the Sub-Trajectory approach is selected to explore the connection between the network partitioning and the variability of travel time.

The slope of the linear relationship between the mean and standard deviation of travel time per unit of distance indicates the degree to which the system reliability degrades with increasing congestion. Here, we explore the impact of the network partitioning on this coefficient. Figure 7 illustrates the relation between the coefficient of reliability with different congestion measures (average density, standard deviation of density, and density coefficient of variation) for the morning (Figure 7(a)) and evening (Fig. 7(b)) peak periods. The horizontal axis shows different cases of clustering for both directional (blue bars) and non-directional (orange bars) approaches with different sizes versus the estimated value for the entire study area network (the green bar). Clusters are sorted based on the increasing order of the reliability measure. Results indicate that for the morning peak period, the coefficient of reliability changes only slightly among the different clusters and remains almost constant. However, this coefficient significantly varies over the clusters in each partitioning approach for the PM peak period (the reliability measure for clusters is in the range of 0.5 to 1.7 times of the measure in the study area network).

The question that arises here is why the results are different for these two time periods. The top two charts show that the average and standard deviation of density cannot address this issue. In the PM peak, the average and standard deviation of density are inversely correlated with the reliability coefficient. However, there is no such pattern in the AM Peak, since the reliability measure is almost constant while the average density and its standard of deviation fluctuate without a specific pattern. The density coefficient of variation, which incorporates the average and standard deviation of density simultaneously, seems to play a key role. The third chart from the top indicates that this variable is directly correlated with the reliability coefficient for both peak periods. It is almost constant in the AM peak, similar to the reliability coefficient, and directly related to the reliability coefficient in the PM peak. Therefore, if we partition the network based on the congestion distribution, it can affect the reliability measure estimation depending on the level of congestion (AM peak vs. PM peak).

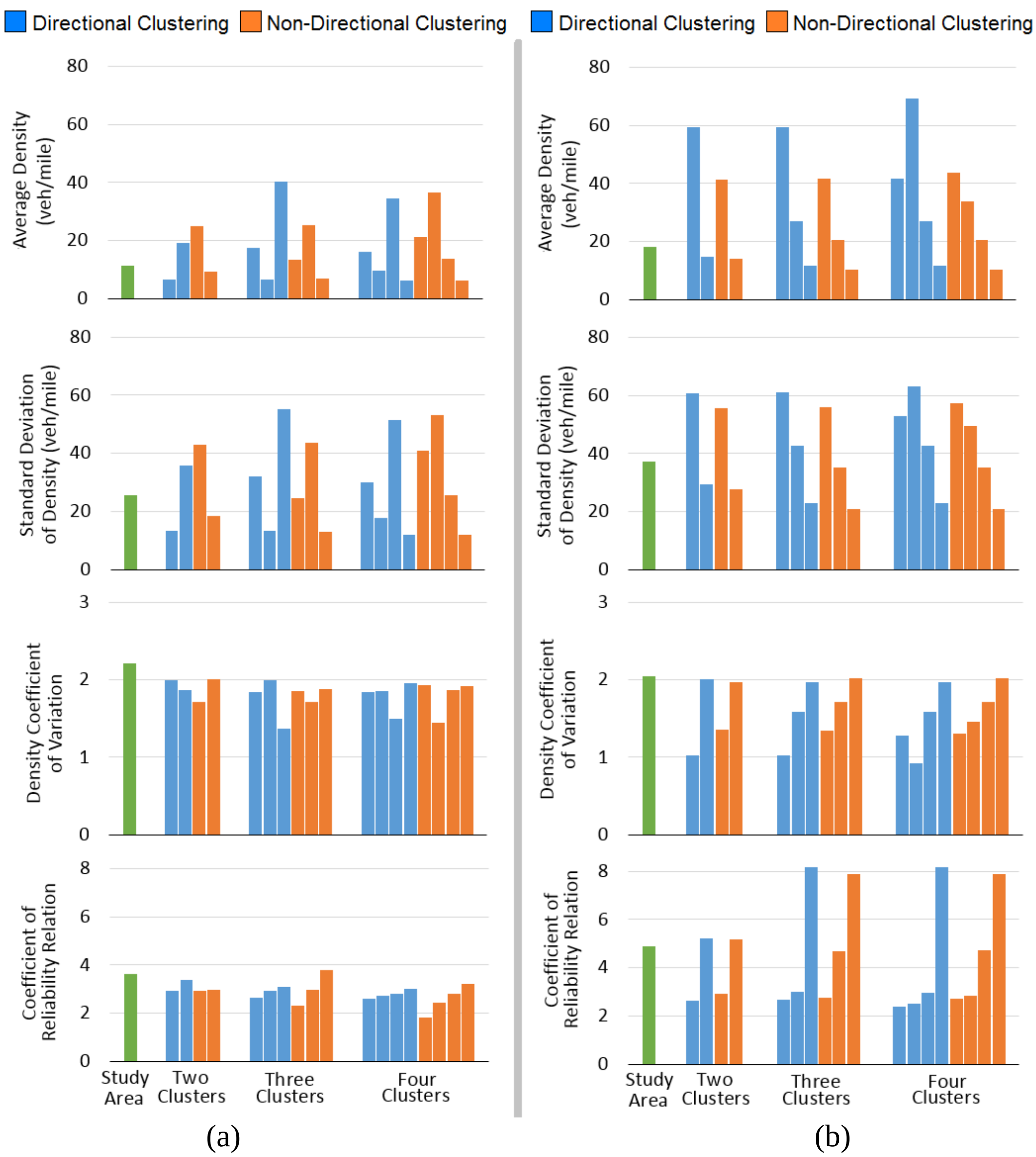


FIGURE 7 Correlation of the coefficient of reliability relation with different congestion measures (average density, standard deviation of density, and density coefficient of variation) and the clustering size during (a) AM Peak Period, and (b) PM peak period

CONCLUSION

Partitioning heterogeneous networks into homogenous clusters is thoroughly studied in the literature to apply innovative control strategies. On the other hand, its impact on network performance quality measures such as reliability has not been studied previously. A linear relation between the mean and standard deviation of travel time per unit of distance has been established in the literature for transportation networks. This study explores the impact of partitioning a heterogeneous network on the estimated travel time reliability measure, as the main contribution. For this purpose, the reliability measure is estimated for the entire heterogeneous network and different clusters generated by employing directional and non-directional partitioning approaches. The impact of these approaches, as well as the number of clusters, on the travel time reliability relation is assessed in this study. Two different approaches are also used to allocate vehicle trajectories to different time intervals in the reliability measure estimation, with different implications for the extent of variability that is captured. Applying and comparing two methodologies for partitioning and two approaches for the reliability measure estimation under different actual demand patterns (AM peak versus PM peak) in an actual large scale network are other contributions of this study.

Vehicle trajectories resulting from 24-hour traffic simulation of the Regional Chicago network are used in analyses for NFD estimation, network partitioning, and travel time reliability measure estimation. The simulation horizon is divided into 5-minute time intervals to capture network dynamics. The network partitioning is implemented for two AM and PM peak periods with 4 hours durations. The key findings from the numerical results are as follows:

- The sub-trajectory approach estimates more robust and higher reliability measures, and considers network dynamics in a more coherent way than the Trajectory approach. It also estimates different values for the AM and PM peak periods, unlike the trajectory approach.
- The directional clustering with size of 3 has the best performance relative to the non-directional approach and other cluster sizes based on the defined partitioning quality measure. This highlights the importance of considering regions with homogeneous level of congestion for aggregated network level modeling.
- The AM clusters have different values for the average and standard deviation of density. However, the density coefficient of variation is almost constant, which results into similar travel time reliability measures for different clusters.
- In the PM peak, there is an inverse relation between the reliability measure, and average and standard deviation of density. While the higher density coefficient of variations indicates more uncertainty in the network.
- The density coefficient of variation is a useful measure to assess impacts of the network partitioning on the reliability measure.

In summary, it is shown that the congestion-dependent partitioning of a heterogeneous network can significantly affect the estimated reliability measure for each sub-network. It is also shown that the density coefficient of variation is a key factor that helps explain the impact of the clustering on the reliability measure estimation. However, these are observations on a single case study. More research with actual data or simulated data from other networks with different configurations and demand patterns are needed to further explore these relations, quantify the impacts of density coefficient of variations, and identify other factors contributing into these relations.

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