Traffic Flow Variation and Network Structure

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Abstract

This study defines and detects competitive and complementary links in a complex network and constructs theories illustrating how the variation of traffic flow is interconnected with network structure. To test the hypotheses, we extract a grid-like sub-network containing 140 traffic links from the Minneapolis - St. Paul highway system. We reveal a real-world traffic network comprises both competitive and complementary links, and there is a negative network dependency between a competitive link pair and a positive network dependency between a complementary link pair. We validate a robust linear relationship between standard deviation of flow in a link and its number of competitive links, its link correlation with competitive links, and its network dependency with both competitive and complementary links. The results indicate the number of competitive links in a traffic network is negatively correlated with the variation of traffic flow in congested regimes as drivers are able to take alternative paths. The results also signify that the more the traffic flow of a link is correlated to the traffic flow of its competitive links, the more the flow variation is in the link. Considering the network dependency, however, it is corroborated that the more the network dependency between a link and its competitive links, the more the flow variation in the link. This is also true for complementary links.

Keywords: Traffic flow variations; Reliability; Competitive links; Weight matrix; Network structure

INTRODUCTION

In investigating traffic system data, an increase in the reliability of traffic links boosts the confidence of system users that the average traffic conditions, such as traffic flow and travel time, represent the typical traffic conditions (1). This interrelationship derives from the statistical expression that the higher the variability of the data, the lower the system reliability becomes. As a result, the road network reliability marries the statistical concept of traffic conditions variability, which has become a substantial component regulating commute route, departure time, and trip linking decisions (2).

Traffic flow variability deteriorates the road network reliability by perplexing the task of monitoring and controlling the operation of road networks and doubling travel uncertainty (3). The road network reliability requires understanding the changing dynamics of traffic flow variation. Monitoring and alleviating traffic flow variability, hence, has caught the attention of operating agencies for the sake of avoiding unexpected delays and ensuring a smooth travel under normal traffic flow fluctuations (4). In parallel, a well-established literature has gradually been documented that contemplates the variation of traffic conditions as a function of spatial and temporal traffic network circumstances including incidents, road construction, weather variations, departure time, fluctuations in demand, and inadequate capacity (5, 6, 7, 8, 9).

Concretely speaking, three distinct components cause variations in traffic conditions (10):

1. Regular condition-dependent variations, which are predictable and a function of time-of-day, day-of-week, and seasonality,

2. Irregular condition-dependent variations, which are unpredictable with an irregular stochastic incident source, and

3. Random variations which, unlike the irregular condition-dependent variations, are not noticeable for an extended period of time and only affect a single trip.

Contrary to irregular condition-dependent variations, regular condition-dependent variations are expected by drivers, and consequently they perform the necessary adjustments to offset the added costs. Interpreting these variations at the link-level has manifold practical applications, including real time dynamic control of traffic systems, congestion and incident detection, and ramp metering, to name a few.

Despite efforts to explain the variation of traffic flows and network reliability, little is known about the association between traffic flow variations and network structure. This deficiency stems from the lack of knowledge about the network dependency between traffic links in a complex network. A real-world traffic network consists of links both in series and in parallel, which are spatially correlated and either compete with or complement each other. The complementary nature indicates that vehicles observed upstream at one time interval will be observed downstream at a later time interval. The competitive nature, however, demonstrates that competitive links bear a significant proportion of diverted vehicles, when one of them is saturated or closed (11, 12). We add to the current knowledge of traffic flow variations by building theories describing how the variation of traffic flow in a link is interconnected with the network structure and its link interdependencies. In particular, we contribute to the literature of network reliability by fulfilling the following objectives:

- Is the variability of traffic flow in a traffic link associated with the number of competitive links?
- Is the variability of traffic flow in a traffic link associated with link dependency?
- Is the variability of traffic flow in a traffic link associated with network dependency?

Answering these questions bolsters the design and evaluation of operation strategies and transportation planning. To test the hypotheses, we extract a sub-network of the Minneapolis - St. Paul highway system. The selected sub-network comprises 140 traffic links with a grid-like configuration that enables us to understand whether and to what extent the competitive traffic links impact the traffic flow variation at the link-level.

COMPETITIVE AND COMPLEMENTARY LINKS

- **Competitive links**: Two links are competitive, if an increase in the cost of one increases the flow of the other.
- **Complementary links**: Two links are complementary, if an increase in the cost of one decreases the flow of the other.

DATA AND NETWORK CONFIGURATION

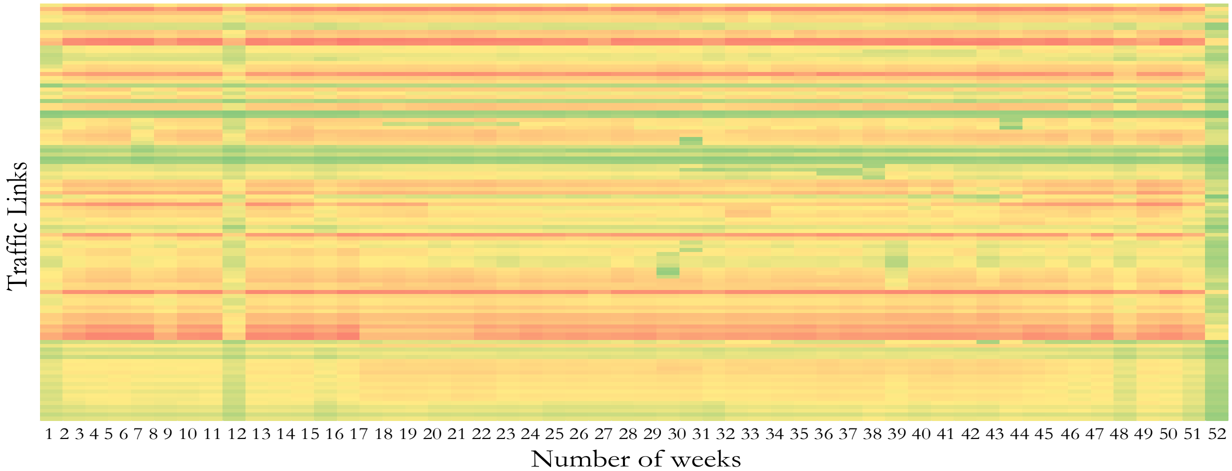
We extracted the data from the Minnesota Department of Transportation's Intelligent Roadway Information System (IRIS), which is an open source advanced traffic management system. The system contains loop and virtual detectors collecting and recording traffic volume every 30 seconds throughout the Minneapolis - St. Paul highway network. For the purpose of analysis, we selected a grid-like network topology that includes both competitive and complementary links. This topology enables us to clearly decompose the role of competitive and complementary links in a reliability assessment. The selected topology consists of 140 traffic links, which are located in major highways in the western suburbs, specifically I-494, I-94, I-394, US 169, TH 212, TH 100, and TH 62 for the East-West and South-North directions.

We are of the opinion that the association between network structure and traffic flow variations is a function of time-of-day and day-of-week. We therefore randomly culled Tuesday as a day-of-week. We then extracted the traffic flow of selected 140 traffic links over 2015 for the following time thresholds at a 30-second time interval:

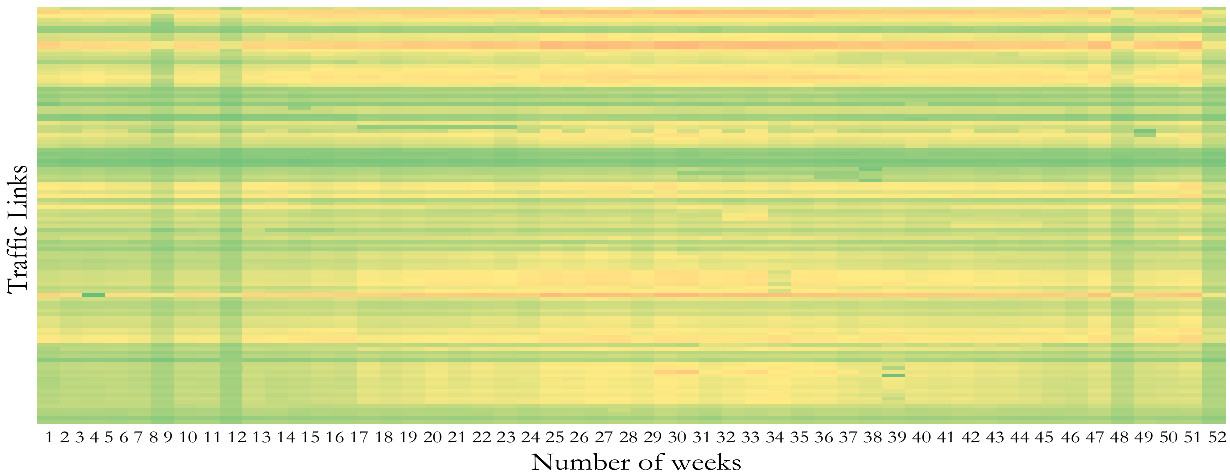
- Morning rush hour: From 7:30-8:30 AM
- Morning non-rush hour: From 10:30-11:30 AM
- Evening rush hour: From 4:30-5:30 PM

In the morning rush hour, traffic flow fluctuates between 529 vehicles per hour and 6,388 vehicles per hour, with an average value of 3,107 vehicles per hour over 140 traffic links in 2015. In the morning non-rush hour, traffic flow ranges from between 182 vehicles per hour and 4,377 vehicles per hour, with an average value of 2,024 vehicles per hour over 140 traffic links in 2015. Akin to the morning rush hour, traffic network experiences a high level of congestion in the evening rush hour between 4:30 PM and 5:30 PM. Traffic flow in this time threshed fluctuates between 119 vehicles per hour and 6,999 vehicles per hour, with an average value of 3,545 vehicles per hour.

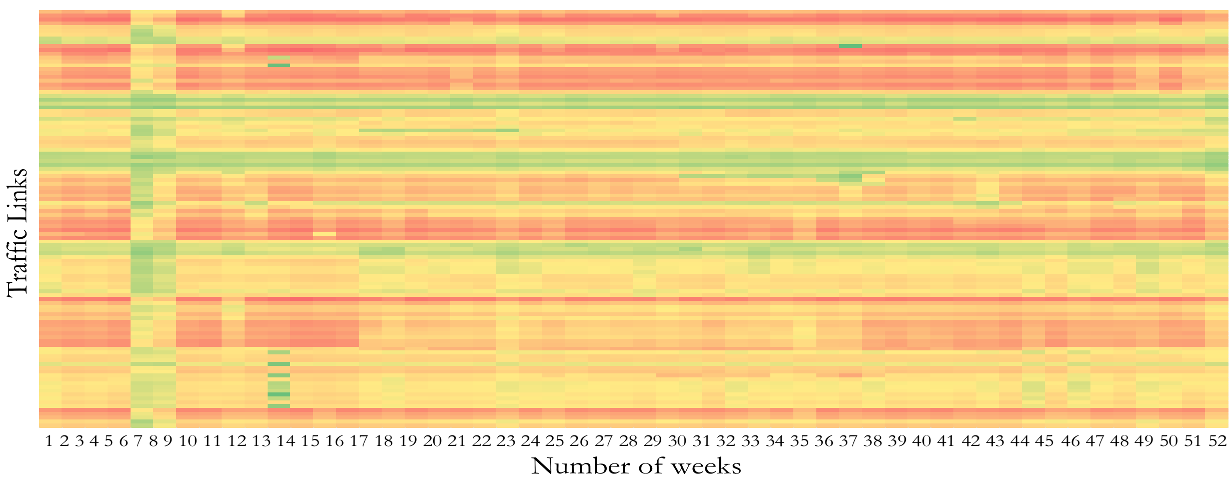
To give the reader a sense of traffic flow variations in each traffic link over a year, we draw the profile of traffic flow in 140 links for all Tuesdays of 2015 in Figure 1. To depict this figure, we smoothed the traffic flow of each link over an hour. This resulted in 52 observations for each traffic link as we extracted the traffic flow of each link over all Tuesdays of 2015. This figure also schematically compares the traffic flow between selected times of day. The color spectrum changes from green, representing the lowest 10 percentile of traffic flow values, to red, representing the highest 10 percentile of traffic flow values. As traffic flow increases in value, the green color approaches yellow, which indicates the 50 percentile of the values. With higher traffic flow, the yellow spectrum then becomes red. Looking at Figure 1, it is found that the traffic flow in the evening rush hour is significantly greater than morning rush hour, and of course non-rush hour. Looking at horizontal lines, it is inferred that the variation of traffic flow over a year is remarkable in some traffic links, particularly in rush hours.



(a) Morning rush hour: 7:30-8:30 AM



(b) Non-rush hour: 10:30-11:30 AM



(c) Evening rush hour: 4:30-5:30 PM

FIGURE 1 : Profile of traffic flow in 140 links for all Tuesdays of 2015

ANALYSIS OF RESULTS

Following the definition of competitive and complementary traffic links and detecting them in the Minneapolis - St. Paul highway system as described in (11), this section tests the three hypotheses postulated earlier in the paper. To measure flow variation in a traffic link, we simply calculate the standard deviation of traffic flow throughout 2015 for each link. The traffic flow is smoothed over an hour for all three time intervals. For example, for the morning rush hour, we aggregated traffic flow of links between 7:30 AM and 8:30 AM for all Tuesdays of 2015. This resulted in 52 flow observations for each link. We then calculated standard deviation of traffic flow of each link over a year. The following subsections represent the results of analysis for each hypothesis.

Variability and Competitive Links in Numbers

The first hypothesis asserts that the variability of traffic flow in a link is negatively correlated with the number of competitive links. In other words, a traffic link with more associated competitive links experiences less traffic flow fluctuation. The reason is more alternative paths are available for drivers to take, which limits the variability of traffic flow in the link. We regress the traffic flow variation in each link against the number of competitive links associated with the study link, which is obtained from the three-dimensional temporal detrending algorithm. Table 1 outlines the results of the regression analysis for all three time intervals.

TABLE 1 : Results of regressing traffic flow variations against number of competitive links

Model	Time of Day	Variable	Coefficient	t-test	P-value	Adjusted R^2
1	Morning	No. Competitive Links	-2.34	-1.68	0.09	0.02
		Constant	485.16	6.53	0.00	
2	Non Rush	No. Competitive Links	0.19	0.14	0.88	0.00
		Constant	254.05	4.44	0.00	
3	Evening	No. Competitive Links	-3.29	-2.08	0.00	0.03
		Constant	617.62	6.90	0.00	

The results indicate a negative correlation between the variability of traffic flow in a link and its number of competitive links in both morning and evening rush hours, as congestion causes traffic flow to switch to competitive paths. This correlation is stronger in evening rush hours. We speculate that traffic demand on Tuesday evenings is significantly higher than Tuesday mornings, resulting in a stronger correlation between the number of competitive links and the variability of traffic flow. Comparing the average traffic flow of both Tuesday evenings and Tuesday mornings in the selected sub-network, we corroborate our hypothesis. The average traffic flow over all links on Tuesday evenings equals 3542 vehicles per hour, while this number equals 3105 vehicles per hour for Tuesday mornings. However, we have not found a significant correlation between the variability of traffic flow in a link and its number of competitive links during the non-rush hour period. Unlike the rush hour period, in which the high level of congestion causes traffic flow to switch to the competitive paths, the low level of traffic congestion during non-rush hour makes switching to the competitive paths unnecessary. As a result, the variation of traffic flow in a link is no longer a function of competitive links.

Variability and Link Dependency

The second hypothesis declares that the variability of traffic flow in a link is negatively correlated with the link dependency in the network. The magnitude of correlation, depends on when the competitive link dependency or complementary link dependency is taken into the consideration. The link dependency is captured in two steps:

- **Step 1:** We correlate the traffic flow of a link with other links.
- **Step 2:** To calculate competitive (complementary) link dependency, we sum the correlations between the study link and its competitive (complementary) pair.

The competitive and complementary links dependencies are formally defined by Equation 1 and Equation 2, respectively.

$$L_i^- = \sum_{j=1}^{J} Cor(\tilde{q}_i, \tilde{q}_j) \tag{1}$$

$$L_i^+ = \sum_{k=1}^{K} Cor(\tilde{q}_i, \tilde{q}_k) \tag{2}$$

Where:
L_i^- (L_i^+) = Competitive (complementary) link dependency
$\tilde{q}_i$ = Vector of traffic flow in link i
J (K) = Number of competitive (complementary) links to link i

The formula helps explains the variation in the flow of traffic. This variation ranges from 0 to 1, which shows the completely independent and completely dependent links, respectively. Obviously, the complementary link dependency is higher than competitive link dependency as the former includes upstream and downstream links, in which the same vehicles are observed multiple times in a certain time period. To test the association between traffic flow variation and link dependency, we regress the link dependency derived from Equation 1 and Equation 2 against the standard deviation of traffic flow over 2015. To juxtapose between the competitive and complementary links dependencies, we develop three different models for each time-of-day interval: (1) A model with only competitive link dependency, (2) A model with only complementary link dependency, and (3) A model including both competitive and complementary links dependencies. Table Hypothesis2 depicts the results of the regression analysis for all three time intervals.

TABLE 2 : Results of regressing traffic flow variations against link dependency

Model	Time of Day	Variable	Coefficient	t-test	P-value	Adjusted R^2
1	Morning	L_i^-	-8.72	-4.84	0.00	0.17
		Constant	558.06	13.28	0.00	
2	Morning	L_i^+	-2.06	-1.40	0.16	0.01
		Constant	451.47	6.94	0.00	
3	Morning	L_i^-	-8.54	-4.59	0.00	0.17
		L_i^+	-0.58	-0.42	0.67	
		Constant	579.40	8.81	0.00	
4	Non Rush	L_i^-	-2.26	-1.32	0.18	0.00
		Constant	210.88	5.25	0.00	
5	Non Rush	L_i^+	1.04	1.03	0.30	0.00
		Constant	203.08	3.49	0.00	
6	Non Rush	L_i^-	-2.02	-1.16	0.24	0.00
		L_i^+	0.84	0.83	0.40	
		Constant	168.22	2.57	0.01	
7	Evening	L_i^-	-10.81	-4.09	0.00	0.13
		Constant	644.59	11.98	0.00	
8	Evening	L_i^+	2.95	1.47	0.14	0.01
		Constant	326.93	4.34	0.00	
9	Evening	L_i^-	-11.04	-4.22	0.00	0.15
		L_i^+	3.34	1.79	0.07	
		Constant	527.11	6.23	0.00	

The results demonstrate that there is a significant negative correlation between traffic flow variation in a link and its competitive links dependency in both morning and evening rush hours. The coefficient of the competitive links dependency in the evening rush hour is greater than the morning rush hour. However, we have not found a significant correlation between the complementary link dependency and traffic flow variation. Akin to the association between the number of competitive links and traffic flow variation during the non-rush hour period, there is not a significant correlation between the competitive link dependency and traffic flow variation in non-rush hour. This echoes the fact that the competitive nature of traffic links becomes meaningful when the traffic network witnesses the high level of congestion.

Variability and Network Dependency

As alluded to in the preceding section, there is a spatial or network correlation between traffic links of a network, which shows up after appropriately removing the temporal dependency between traffic links. Not only does this "network dependency" between two links vary according to the sign, but it also varies according to the magnitude. The positivity and negativity network dependency identifies competitive and complementary nature of traffic links. However, the magnitude of dependency determines the criticality of the link as it speaks for the extent to which the links of a network are dependent on the existence of the link in question.

The third hypothesis articulates that the variability of traffic flow in a link is positively correlated with the network dependency in a traffic network. Concretely speaking, the more network dependency exhibits the more vulnerability, and consequently the more traffic flow variation. The network dependency is affected by the number of competitive and complementary links associated with the link in question as corroborated earlier in the first hypothesis testing. We therefore capture this effect using Equation 3 and Equation 4.

$$N_i^- = \frac{\sum_{j=1}^{J} \left|\hat{s}(l_i, l_j))\right|}{j} \tag{3}$$

$$N_i^+ = \frac{\sum_{k=1}^{K} \hat{s}(l_i, l_k))}{k} \tag{4}$$

Similar to link dependency, we intend to discriminate between the competitive and complementary network dependencies. Hence, we develop three different models for each time-of-day interval: (1) A model with only competitive network dependency, (2) A model with only complementary network dependency, and (3) A model including both competitive and complementary network dependencies. Table 3 outlines the results of the regression analysis for all three time intervals.

TABLE 3 : Results of regressing traffic flow variations against network dependency

Model	Time of Day	Variable	Coefficient	t-test	P-value	Adjusted R^2
1	Morning	N_i^-	26.64	4.75	0.00	0.17
		Constant	187.85	4.90	0.00	
2	Morning	N_i^+	58.94	3.28	0.00	0.08
		Constant	38.54	0.38	0.69	
3	Morning	N_i^-	22.71	3.48	0.00	0.17
		N_i^+	23.5013	1.18	0.23	
		Constant	84.67	0.88	0.37	
4	Non Rush	N_i^-	39.09	2.65	0.00	0.05
		Constant	147.44	3.31	0.00	
5	Non Rush	N_i^+	69.38	3.43	0.00	0.09
		Constant	-94.94	-0.90	0.36	
6	Non Rush	N_i^-	27.72	1.87	0.06	0.11
		N_i^+	58.88	2.83	0.00	
		Constant	-122.18	-1.17	0.24	
7	Evening	N_i^-	59.7260	7.79	0.00	0.35
		Constant	69.6136	1.42	0.15	
8	Evening	N_i^+	67.1910	2.53	0.01	0.04
		Constant	66.2842	0.45	0.65	
9	Evening	N_i^-	58.6040	7.86	0.00	0.39
		N_i^+	58.0396	2.74	0.00	
		Constant	-241.744	-1.96	0.05	

The results corroborate our hypothesis. Both competitive and complementary network dependencies are positively correlated with traffic flow variation. The competitive dependency plays a more significant role than the complementary dependency during the rush hour period. This role is flipped during the non-rush hour period. Looking at Model 9, it is inferred that the complementary dependency is more significant than the competitive dependency. Comparing the goodness-of-fit of the models, we further find that the network dependency describes traffic flow variation more accurately, when network experiences the higher level of congestion.

SUMMARY AND CONCLUSIONS

The increasing need for monitoring and improving the reliability of transport systems has fueled the interest of researchers and practitioners to examine the variability of traffic conditions. Understanding the variability of traffic conditions assists operating agencies to calibrate their capabilities through the lens of intelligent transportation systems. It is not surprising then that a burgeoning literature has documented investigating the variation of traffic conditions as a function of temporal and spatial network characteristics. There is still little evidence, however, linking the variation of traffic flow with the structure of network. We revealed there is a structural way to deal with traffic networks, which facilitates using network peculiarities to explain the variation of flow in a scale free or independent manner.

In particular, this study established a connection between traffic network structure and traffic flow variation at the link level on a real-world traffic network, which has the potential of being used for constructing and controlling road networks, modeling of network travel time reliability, and boosting reliability of travel in a network. The selected network was a grid-like sub-network containing 140 competitive and complementary links, which extracted from the Minneapolis - St. Paul highway system. This research tested how and to what extend network structure explains the variation of flow in a traffic link. The paper validated a robust linear relationship between standard deviation of flow in a link and its number of competitive links, its link correlation with competitive links, and its network dependence with both competitive and complementary links. Through use of computational results of different time-of-day intervals, this paper confirmed that well-established relationships between the structure of the network and traffic flow variation are a function of traffic regimes. We encapsulate the key findings:

- A real-world traffic network is comprised of both competitive and complementary links. The network dependency, which is a function of physics of the network, forms a negative correlation between a competitive link pair and a positive correlation between a complementary link pair. The magnitude of network dependency is associated with time-of-day, in which there is a stronger competitive network dependency in congested regimes and a stronger complementary network dependency in uncongested regimes.

- The existence of competitive links enables drivers to switch to alternative paths, when they experience the high level of congestion. Immediately, we revealed the number of competitive links in a traffic network is negatively correlated with the variation of traffic flow in congested regimes as drivers are able to take alternative paths. In uncongested regimes, however, this relationship is insignificant as there is no congestion effect to shift or stall traffic.

- The sum of correlations between the traffic flows of each competitive link pair explains the variation of flow in traffic links. The results signified that there is a negative correlation between the link correlation and the flow variation at the link level. In other words, the more the traffic flow of a link is correlated to the traffic flow of its competitive links, the more the flow variation is in the link. This association is insignificant in the uncongested traffic regimes.

- The network dependency introduced in the current empirical study identifies the criticality of a link, which is positively correlated with the variation of traffic flow at the link level. The more the link is physically dependent to its competitive links, the more the flow variation in the link. This is also true for complementary links. However, the competitive network dependency has remarkably more potential to explain the traffic flow variation in congested regimes. In uncongested regimes, the potential of competitive network dependency is defeated by complementary network dependency. The reason is the nature of competitive links becomes trivial in uncongested traffic regimes.

As the theories and methodologies introduced in this paper contemplated how the variation of traffic flow is interconnected with the structure of network, this provides insights and a solid foundation for future research avenues. The following suggestions are made for further research:

- This study is devoted to explain how traffic flow variations at the link level are benefiting from the structure of network. There is, however, much scope to broaden the range of implementation of these theories and methodologies on other traffic conditions including travel time and traffic speed.

- Although this research employed the network dependency with theoretical assertions for explaining the variation of traffic flow, it is envisaged that the proposed method to extract network dependency could find a wide range of applications in traffic forecasting during predictable and unpredictable incidents. Hence, a research avenue is open for further validation in follow-up traffic forecasting studies.

- For testing the hypotheses postulated in this research, Tuesday was randomly selected as a representative of weekdays. This study also targeted to unravel whether there is a significant difference between the network dependency in morning rush hour, evening rush hour, and non-rush hour. Future research may benefit from the methodology introduced in this research and broadens the conclusions more, if not all, days and times.

- This study took the long-term flow variation into consideration, as it analyzed the standard deviation of traffic flow in each link over a year. A research avenue is open for using testing how the short-term traffic flow variation is explained by physics of network and its link interdependencies.

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