Philippine Journal of Science
148 (1): 51-62, March 2019
ISSN 0031 - 7683
Date Received: 14 Jun 2018

Ideal Flow Traffic Analysis: A Case Study on a Campus Road Network

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Traditional traffic assignment models often use historical travel demand, such as the costly origin-destination flow distribution and actual flow distribution, as inputs in determining the most efficient distribution of flow on a road network. In this paper, the authors examine the ideal flow network (IFN) model, a novel and alternative traffic assignment model. The IFN model is compared with a traditional traffic assignment model using a generic model comparison method. The application of the method is presented using a campus road network as a case study to examine the importance of understanding the road network structure – by making a comparison between the results of a traditional traffic assignment model and the IFN model to gain nuanced insights into the distribution of the traffic flow. The authors suggest that – while both models can yield almost the same result – the IFN model has the advantage of using a stochastic matrix, which is more readily available than demand data. The IFN model is likewise more geared toward evaluating the ideas of solving the traffic problem through simulation modeling, which – as a form of social engineering – is easier to stabilize into traffic management.

Keywords: ideal flow analysis, traffic analysis, traffic assignment model

INTRODUCTION

Traffic congestion has always been a perennial problem, especially on important roads such as those located in densely populated metropolitan areas. The problem of congestion is not easy to handle, and varied solutions have been suggested and implemented to address the challenge. These solutions necessitate the creation of, or the improvement of, existing traffic assignment models. Traditional traffic assignment models make use of historical travel demand data, specifically from the costly origin-destination (OD) survey. This is a difficulty for low-income societies, especially those with limited OD data or minimal budget for data collection. It is beneficial, therefore, to view traffic assignment from both sides of supply (road infrastructure) and demand rather than merely from the demand side. This is the uniqueness and novelty of the Ideal Flow Network (IFN) model (Teknomo 2017, Teknomo and Gardon 2017). The IFN models the ideal flow matrix with which one can measure the efficiency of the current traffic flow. In other words, one can use the flow matrix generated by the model as a guide to how the current traffic flow should be managed.

The goals of this paper are three-fold. First, to provide a generic way of comparing two models that have only partially the same input but have the same output. Second,

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to implement this generic concept of model comparison by comparing a traditional traffic assignment model with the IFN model. Third, to present how the IFN model can be used to simulate traffic flow on a real-world road network when a traffic scheme change – such as changing a two-way road to a one-way road – is applied. The results are compared to flow obtained from applying an incremental traffic assignment method – one that makes use of OD data.

Related Concepts

Traffic assignment. Traffic assignment is the procedure of allocating flow into the network following certain rules. These rules are usually rooted on route-choice behavioral principles (Patriksson 2015), the most famous of which are known as Wardrop's principles (Wardrop 1952) – considered as the standards for traffic assignment modelling. The two principles are called the **user equilibrium** (UE) and the **system optimum** (SO) traffic assignment models. Krylatov *et al.* (2016) investigated and presented the relationship of these principles with game theory. In the UE model, which can be likened to Nash's equilibrium, each driver non-cooperatively finds ways to minimize his/her own travel costs (Kitamura *et al.* 2009). In other words, no driver can unilaterally reduce his/her travel costs by shifting to another route. In the SO model, which can also be considered as being under the state of Pareto optimality, the drivers cooperate in choosing routes so that the whole system minimizes its travel time. In applying both principles, it is assumed that travelers have perfect information of the road network *i.e.*, knowledge of all possible routes and the total travel time using each of the route. Thus, there is a need to develop stochastic models – one that takes into account the randomness of route choices of travelers (Daganzo and Sheffi 1977).

When applying these traditional traffic assignment models, the OD flow and the actual flow are necessary as inputs. There are direct and indirect ways of determining the flow count on each link of a road network. The direct way, on the one hand, is to count the number of vehicles that pass through each link at a specific time of day. Recent technologies have now been in use to increase efficiency and decrease human error in gathering data in this way. Toth *et al.* (2013) developed an Android application where data collectors were allowed to review and correct gathered counts through a video. Yuan *et al.* (2013), Yang *et al.* (2017), and Seo and Kusakabe (2015) counted trajectories via GPS devices installed on vehicles. The indirect way, on the other hand, is done by utilizing the *historical* demand flow data – such as OD data – and then use traffic assignment models to generate the flow as discussed by Bell and Lida (1997) and Ortúzar and Willumsen (2011). Another indirect way is to apply the mathematical relationship between a generalized OD matrix and the flow matrix as proposed by Teknomo and Fernandez (2014).

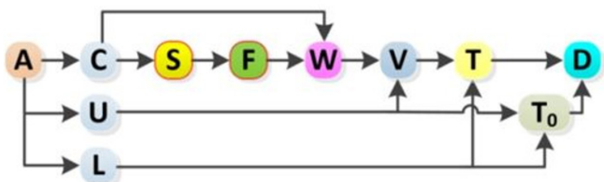
For most of these traffic assignment models, the OD flow and the actual flow are used as input which – more often than not – take a considerable amount of time to gather and analyze. Moreover, most models also assume that travelers have perfect information of the current traffic situation. The IFN model can generate a close enough estimate of the current traffic flow just by using as input a stochastic matrix – which is more readily available than demand data – since it can be obtained from various sources such as the OD matrix itself, information from GPS, and even directly from the road network map (Teknomo and Gardon 2017).

Ideal flow network model. The IFN model aims to determine the best distribution of traffic flow such that the links on a network structure are optimally utilized. It is a novel traffic assignment model that makes use of traffic supply information and allows better flow estimation if real time traffic demand information is available.

In the model, a directed graph is a representation of a road traffic network where nodes represent origins, destinations, and/or intersections; links represent roads; and link weights represent travel time, distances, capacities, traffic flow, among others. This graph representation is the traffic supply information (*i.e.*, network structure) that is utilized to make estimates of the current traffic flow.

In order to apply the model, the directed network graph must be strongly connected, and that flows are conserved in all nodes. When a network is not strongly connected, it can be made so by adding dummy cloud nodes and dummy links as described by Teknomo and Gardon (2017). Furthermore, the model assumes that the best distribution of traffic flows follows the uniform distribution (Gardon and Teknomo 2017) *i.e.*, *the most efficient utilization of a network occurs when flows are uniformly distributed over time and space*. This fundamental assumption of the model (Gardon and Teknomo 2017) is based on the principle of maximum entropy. The flows are not uniformly distributed **spatially** – when one lane is almost empty while the opposite lane is filled to capacity (this happens when travelers go to school or to a workplace from their respective homes, for example), or **temporally** – when congestion occurs during the highest volume of traffic or what is called "rush hour." Since a traveler's route choice is mostly a stochastic behavior and – since in traffic assignment, there is limited or no information at all regarding the behavior of travelers or the current state of congestion of roads – the principle of maximum entropy, which states that the probability distribution with the largest lack of order or predictability best represents the current state of knowledge on the behavior of travelers, provides a way in determining a probability distribution that avoids bias and yet satisfies given constraints (Jaynes 1957).

Figure 1 shows the framework of the model (Teknomo and Gardon 2017):



A: Adjacency matrix	**W**: Flow/Capacity ratio matrix
C: Capacity matrix	**V**: Link speed matrix
U: Link maximum speed matrix	**T**: Travel time matrix
L: Link distance matrix	$\mathbf{T_0}$: Minimum travel time matrix
S: Stochastic matrix	**D**: Delay matrix
F: Flow matrix	

Figure 1. Ideal flow framework for traffic assignment in matrix form (Teknomo and Gardon 2017)

Utilizing the traffic supply information, the stochastic transition matrix $\boldsymbol{S}$ is defined to be the ratio between the capacity of a link from one node and the sum of all the capacities of the links from the same node:

$$\mathbf{S} = [s_{ij}] = \frac{c_{ij}^{\alpha} e^{\beta c_{ij}}}{\sum_{j=1}^{o_i} c_{ij}^{\alpha} e^{\beta c_{ij}}} \tag{1}$$

where $\mathbf{C} = [c_{ij}]$ represents the link capacity matrix. Eq. (1) is also termed as *proportional capacity*.

The probability distribution model described by Eq. (1) has two parameters: α and β. Notation $e = 2.7172 \ldots$ is the Euler number. This basic form of the new model of generalized proportional capacity is similar to the model of generalized cost (Ortúzar and Willumsen 2011). Note that β is always negative. Eq. (1) is based on the property of deterrence functions (Ortúzar and Willumsen 2011), where a negative value of β represents a "disincentive" to travel when costs increase. While it is possible to set the value of α and β for each node, for simplicity, it is advisable to use a single value of α and a single value of β for the entire network. Calibrating the values of parameters of α and β requires data from several intersections and, with enough sampling, their values can be inferred for all intersections in the network.

To derive the ideal flow matrix **F**, the node probability stationary distribution $\boldsymbol{\pi} = [\pi_{ij}]$ is first computed by solving Eq. (2) using singular value decomposition (SVD) (Golub and Kahan 1965). In this equation, $\mathbf{I}$ is the identity matrix and $\mathbf{j}^T = [1 \quad \ldots \quad 1]$:

$$\begin{bmatrix} \mathbf{S}^T - \mathbf{I} \\ \mathbf{j}^T \end{bmatrix} \boldsymbol{\pi} = \begin{bmatrix} \mathbf{0} \\ 1 \end{bmatrix} \tag{2}$$

Then, the ideal flow matrix $\mathbf{F} = [\mathbf{f}_1^T \quad \ldots \quad \mathbf{f}_n^T]$ is obtained from:

$$\mathbf{f}_i^T = \pi_i \mathbf{s}_i^T \text{ for } i = 1..n \tag{3}$$

Seneta (2006) proved the convergence and uniqueness of an irreducible stochastic matrix, thus guaranteeing the existence and uniqueness of $\boldsymbol{\pi}$. The ideal flow matrix, therefore, is unique for each stochastic matrix since $\boldsymbol{\pi}$ is unique (Häggström 2002). Examples and details on the computation of the ideal flow matrix can be read in the article of Teknomo and Gardon (2017).

METHODS

Generic Model Comparison

In this section, a proposed generic model comparison framework will be presented. A generic model can be represented as a function f with a set of input $\mathbf{X}$ and set of parameters $\boldsymbol{\alpha}$ to produce a set of output $\mathbf{y}$:

$$\mathbf{y} = f(\mathbf{X}, \boldsymbol{\alpha}) \tag{4}$$

Using the model, at least three things could be done:

1. Understand a phenomenon.
2. Make a prediction.
3. Control or optimize.

When the input data $\mathbf{X}$ and the output data $\boldsymbol{y}$ are known, and the model f is set, the model can be calibrated (*i.e.*, training, learning) to produce any underlying phenomena behind it, which is the set of parameters $\boldsymbol{\alpha}$. Understanding the role of parameters in a model (*e.g.*, sign, value, gradient, and significance of each parameter) would lead to an understanding of the behavior of the model. When a prediction about the output $\boldsymbol{y}$ is made based on the given input data $\mathbf{X}$, it is implicitly assumed that the model f does not change and the set of parameters $\boldsymbol{\alpha}$ is invariant. Using the model to control or optimize means finding the possible input $\mathbf{X}$ for the given target output $\boldsymbol{y}$. Similar to the prediction, in optimization, implicit assumptions are made that the inverse of the model f^{-1} exist and does not change and the set of parameters $\boldsymbol{\alpha}$ is still invariant.

Now, suppose two models f_1 and f_2 are to be compared. There are two ways to compare them:

1. Set the same input $\mathbf{X}$ and calibrate with the same set

of parameters $\boldsymbol{\alpha}$:

$$\mathbf{y}_1 = f_1(\mathbf{X}, \boldsymbol{\alpha})$$
$$\mathbf{y}_2 = f_2(\mathbf{X}, \boldsymbol{\alpha}) \tag{5}$$

The two models would hopefully produce almost the same output:

$$\|\mathbf{y}_2 - \mathbf{y}_1\| < \varepsilon \tag{6}$$

2. Set the same input and calibrate in a way such that the output would be almost equal, or at least the difference between the two outputs would be minimal. The results of such comparison would be different sets of parameters needed to be interpreted further.

The first method of comparison above can only be performed when the models are almost the same in terms of input and parameters. When two different models have significantly different sets of parameters, and have different sets of input variables, then this first type of technique of comparison will not be adequate. Thus, the second way of comparison must be considered.

The second method of model comparison is more reasonable. Suppose we have two models f_1 and f_2 that produce similar output structures $\mathbf{y}_1$ and $\mathbf{y}_2$. Both models contain the same partial input $\mathbf{X}_1$ and the same partial parameter $\boldsymbol{\alpha}_1$. Suppose the partial input $\mathbf{X}_2$ and the partial parameter $\boldsymbol{\alpha}_2$ are unique for model f_1, while the partial input $\mathbf{X}_3$ and the partial parameter $\boldsymbol{\alpha}_3$ are unique for model f_2. Assume also that there is a way to compute $\mathbf{X}_3$ from $\mathbf{y}_2$, with either through the inverse function ${f_2}^{-1}$ or through other means. Then:

$$\mathbf{y}_1 = f_1(\mathbf{X}_1, \mathbf{X}_2, \boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2) \tag{7}$$

$$\mathbf{y}_2 = f_2(\mathbf{X}_1, \mathbf{X}_3, \boldsymbol{\alpha}_1, \boldsymbol{\alpha}_3) \tag{8}$$

To make a reasonable comparison between the two models, the proposed strategy is to set one of the models – say f_1 – as the basis of comparison. Compute $\mathbf{y}_1$ based on Eq. (7) and then set $\mathbf{y}_2 = \mathbf{y}_1$ to compute $\mathbf{X}_3$. After that, compute $\hat{\mathbf{y}}_2 = f_2(\mathbf{X}_1, \mathbf{X}_3, \boldsymbol{\alpha}_1, \boldsymbol{\alpha}_3)$ by calibrating parameter $\boldsymbol{\alpha}_3$. The goal is to determine whether $\hat{\mathbf{y}}_2 = \mathbf{y}_1$ can be actually obtained. Alternatively, at least, there will be a minimal difference between the two outputs. Using this second way of comparison, the following can now be set as a hypothesis:

$$\|\hat{\mathbf{y}}_2 - \mathbf{y}_1\| < \varepsilon \tag{9}$$

For a small positive threshold $\varepsilon > 0$.

Comparison of Traffic Assignment and Ideal Flow Model

In this section, the generic model comparison described in the previous section is utilized into a case study of traffic assignment model (TA) and IFN model. The notations of the generic model comparison are substituted into the actual notations that will be used for TA and IFN.

In this case, model f_1 represents the TA model and model f_2 represents the IFN model. The strategy to make reasonable comparison between the two models is to set the TA as the basis of comparison. Both models have the same output, which is the set of link flows. Both models also have the same partial input – $\mathbf{X}_1$ that represents the network structure (*i.e.*, connectivity, capacity, length, number of lanes) that in turn would have the same network structure parameters $\boldsymbol{\alpha}_1$ (*i.e.*, free flow speed and maximum density). The network structure $\mathbf{X}_1$ is then implemented as an adjacency matrix $\mathbf{A}$ and capacity matrix $\mathbf{C}$. The TA model has an additional input $\mathbf{X}_2$ that represents the OD matrix, and another set of parameter $\boldsymbol{\alpha}_2$ to be calibrated based on real world data (*e.g.*, capacity parameters, cost function parameters). Both TA and IFN have the same input of network structure, which include the capacity and length of each link, and these network structure also influence the same parameters on the free flow speed and maximum density. TA has one additional input requirement that IFN does not need, which is the OD matrix. Thus, the IFN model requires the network structure parameter $\mathbf{X}_1$ but it does not require OD matrix $\mathbf{X}_2$. The OD matrix can be translated into the stochastic parameter $\mathbf{X}_3$. In IFN terminology, the stochastic parameter $\mathbf{X}_3$ is denoted as the stochastic matrix $\mathbf{S}$. The IFN calibration parameter would be the scaling factor $\boldsymbol{\alpha}_3 = \kappa$. The output $\mathbf{y}$ would be denoted by flow matrix $\mathbf{F}$.

Then, compute the flow $\mathbf{F}_a$ based on TA and then form stochastic matrix $\mathbf{S}_f$ from the flow computed based on TA. From the stochastic matrix $\mathbf{S}_f$, compute the flow matrix $\mathbf{F}_b$ using IFN. The ideal flow matrix $\mathbf{F}_b$ should be close to the flow matrix $\mathbf{F}_a$, which was computed *with* the guidance of the OD matrix. Next, compute the flow matrix $\mathbf{F}_c$ using IFN *without* the OD matrix as an input. In this case, form stochastic matrix $\mathbf{S}_c$ based only on the network structure and capacity. Of course, for both of the IFN cases, the scaling factor κ needs to be calibrated such that the sum of square difference of each link flow would be minimized. That is, calibrate the IFN model such that:

$$\kappa_b^* = \underset{\kappa}{\operatorname{argmin}} \|\mathbf{F}_b(\kappa) - \mathbf{F}_a\| \tag{10}$$

and

$$\kappa_c^* = \underset{\kappa}{\operatorname{argmin}} \|\mathbf{F}_c(\kappa) - \mathbf{F}_a\| \tag{11}$$

For this calibration, the coefficient of determination – which is defined in Eq. (12) – can be measured:

$$R^2 = 1 - \frac{SSE}{SST} \qquad (12)$$

The SSE is the sum of squares of the error between the two flows being compared, while SST is the square mean difference of $\mathbf{F}_a$.

The distribution of the three flows in pairs, $\mathbf{F}_b\ (\kappa_b^*)\ vs\ \mathbf{F}_a$, $\mathbf{F}_c\ (\kappa_c^*)\ vs\ \mathbf{F}_a$, and $\mathbf{F}_c\ (\kappa_c^*)\ vs\ \mathbf{F}_b\ (\kappa_b^*)$, are then compared. From the flow matrix, flows can be scaled into other performance indices based on the same network structure input. Since some readers are more at ease interpreting results based on level of congestion and speed, such comparisons will be provided as well. Both TA and IFN use the same cost function, which is based on a US Bureau of Public Roads (BPR) manual (BPR 1964).

CASE STUDY

To implement the concepts discussed in the previous sections, a real world transportation network of the Ateneo campus was used. The case study of the Ateneo campus network was selected based on the availability of the data and the familiarity of the authors who made a previous study in the same location (Franco *et al.* 2012).

Road Network Map

The Ateneo de Manila University (AdMU) Campus Network Map was used as a case in which a traditional traffic assignment and the ideal flow analysis were applied for comparison. A road inventory survey was done to produce a scaled model map of the area, and to determine the capacity of the network being studied in terms of road length and width. Details on how the survey was performed can be found in the study (Franco *et al.* 2012).

The campus network, located in a major ring road of Metro Manila called *circumference road number five* or *C5,* has a land area of about 80 ha. Figure 2 represents the road network map. The campus hosts about 18000 faculty members, students, and staff.

Figure 3 shows the existing road network (base scenario) before changing two-way roads to one-way roads. It has 76 nodes and 136 links with 21 basins. The network was calibrated based on transportation supply information (*i.e.*, the road capacity, distance, and maximum speed of each link). The values of the parameters α and β in Eq. were set to 1 for simplicity.

Each link connects a start node and an end node. If a road is a two-way road, it is represented by two links. Based on a moving vehicle observer survey (Franco *et al.* 2012), the maximum speed on links inside the campus is 30 km per hour and the maximum speed on links outside (along the Katipunan Avenue portion of C5) is 100 km/hr. The maximum speed for vehicles passing through U-turn slots is assumed to be 20 km/hr. Dummy links are added to connect source or sink nodes. Dummy links can be recognized by being assigned equal link lengths and link widths, which are set to 10.1 m.

A car volume survey and a vehicle type distribution survey were done to produce data on actual traffic flow set at certain locations in the area being studied (Franco *et al.* 2012). One of the conclusions from these surveys is that the maximum volume in the area is 13,000 passenger-car-units per hour (pcuph).

Figure 2. AdMU campus network map (Franco *et al*. 2012)

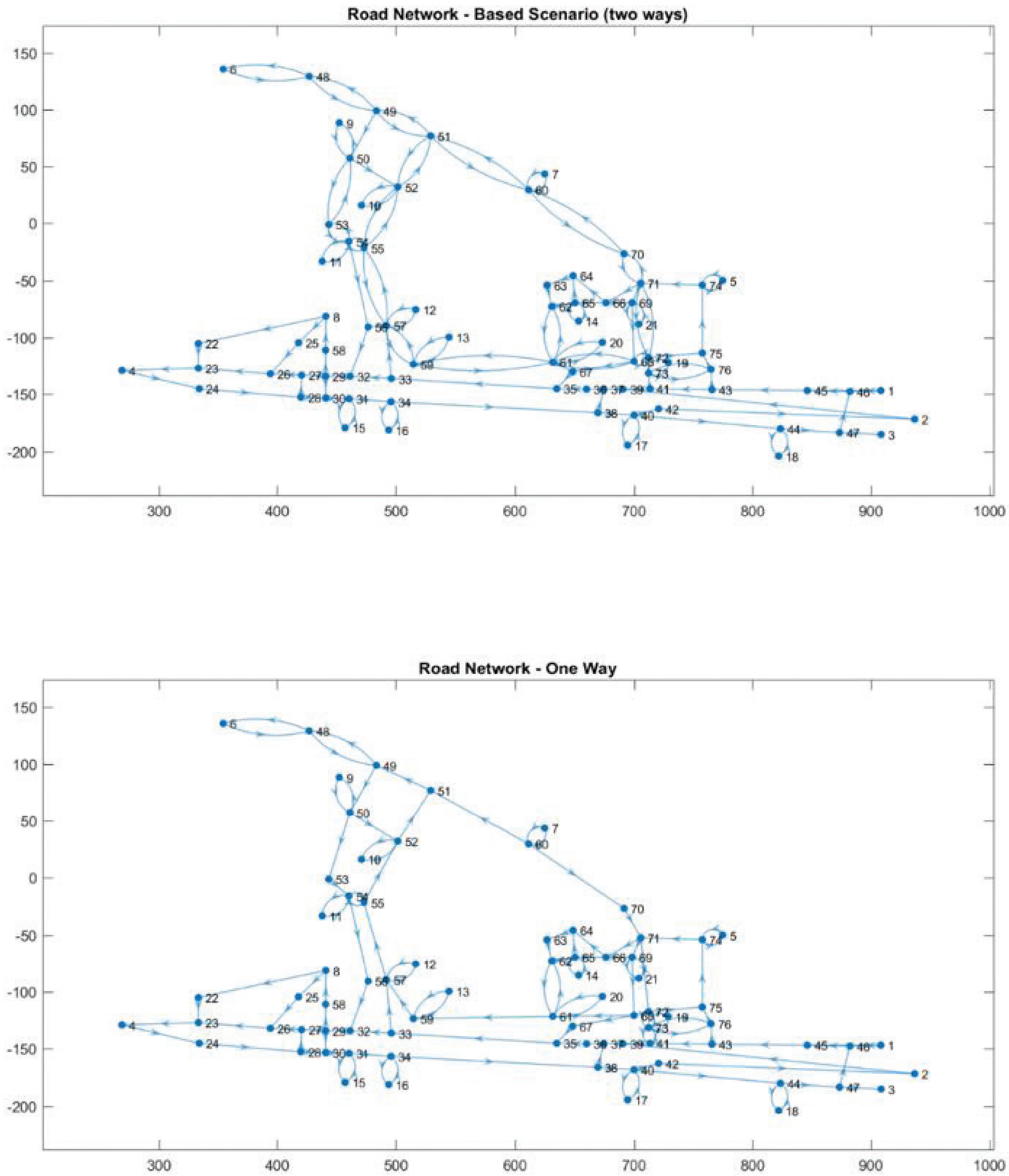


Figure 3. AdMU network graph (base scenario and one-way scenario).

To be able to construct the OD distribution of flow to and from major attractions in the area under study, about 150 hired professional surveyors performed a license plate matching survey for two days – from 6:00 AM to 6:00 PM. The OD result is shown in Figure 4 and in Table 1 (Franco *et al.* 2012). Table 1 indicates that the majority of the volume going to the AdMU campus come from either the south or north direction.

A base traffic scenario was developed (see Figure 5). The simplified map shows the components and the traffic scheme on the campus network.

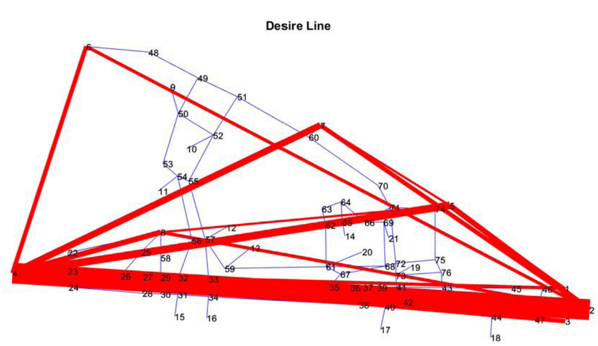


Figure 4. Desire line (Franco *et al*. 2012)

Table 1. Origin destination matrix.

	Daily OD	Origin						
		Marikina/East	Eastwood/South	Aurora/West	UP/North	Miriam	Ateneo	Total
Destination	Marikina/East	0.00%	2.03%	1.01%	1.83%	0.27%	1.41%	6.55%
	Eastwood/South	0.00%	0.00%	5.28%	9.87%	1.11%	11.02%	27.28%
	Aurora/West	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	UP/North	0.00%	18.23%	9.42%	0.00%	2.42%	13.56%	43.63%
	Miriam	0.00%	1.58%	0.71%	1.47%	0.00%	1.01%	4.77%
	Ateneo	0.00%	6.95%	3.37%	6.51%	0.94%	0.00%	17.77%
	Total	0.00%	28.79%	19.79%	19.68%	4.74%	27.00%	100.00%

Traffic Assignment

The traffic assignment model applied requires the following data as input (Franco *et al.* 2012):

- the road network map with the capacity derived from the road inventory and moving vehicles surveys;
- the OD flow distribution, which was multiplied by the maximum hourly flow; and
- the actual flow distribution.

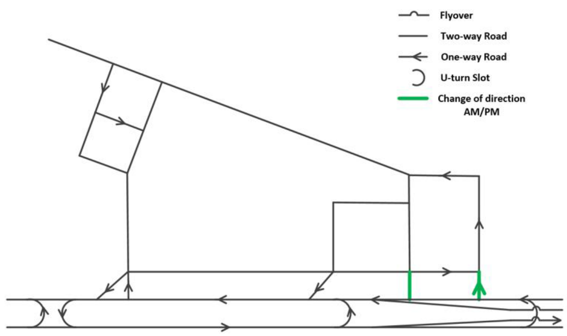


Figure 5. Base scenario (Franco *et al*. 2012)

The traffic assignment was done by incrementally loading the network with small amounts of OD flow data. The OD flow is then assigned into the network, and the cost in terms of travel time is updated before the next incremental loading of the OD flow. This algorithm almost simulates the real world condition where, as time passes, more of the traffic volume will be diverted away from the shortest path. Figure 6 illustrates this algorithm.

A calibration parameter search for the proper multiplication factor to the OD flow was made so that the maximum hourly flow will be close enough to 9050 pcuph. The scaling multiplication factor to the OD flow was found to be 0.778026.

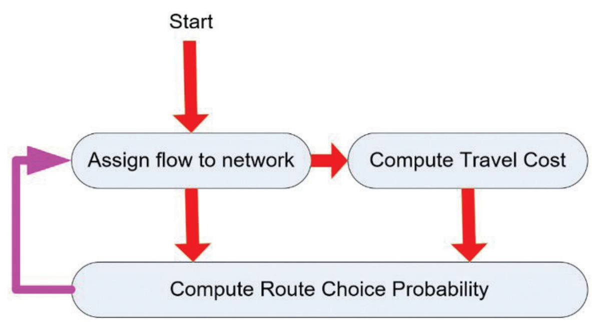


Figure 6. Iterative procedure of a traditional traffic assignment (Teknomo 2008).

Ideal Flow Analysis

The base scenario went through the ideal flow analysis with a change that the first 21 nodes are connected to the cloud node. All 21 basin nodes have two-way dummy links to the cloud, except for nodes 1 and 3. There is only one dummy link from node 1 to the cloud node, and one dummy link from the cloud node to node 3.

The flow matrix $\mathbf{F}_a$ result from the traffic assignment model is converted into stochastic matrix $\mathbf{S}_f$. The ideal flow matrix $\mathbf{F}_b$ can be computed from $\mathbf{S}_f$ based on Eqs. (2) and (3) as the flow matrix guided by the values from the OD matrix. If notation $\oslash$ indicates element-wise division (Hadamard Division) with agreement that 0/0 is 0, then:

$$\mathbf{S}_f = \mathbf{F}_a \oslash (\boldsymbol{\pi}\mathbf{j}^T) \quad (12)$$

The stochastic matrix $\mathbf{S}_c$ can be computed directly from the capacity matrix $\mathbf{C}$. The ideal flow matrix $\mathbf{F}_c$ can be computed from $\mathbf{S}_c$ based on Eq. (2) and Eq. (3) as the flow matrix without the need of the OD matrix.

$$\mathbf{S}_c = \mathbf{C} \oslash (\mathbf{C}\mathbf{j}\mathbf{j}^T) \quad (13)$$

RESULTS AND DISCUSSION

Traffic Assignment

The results of the incremental traffic assignment are shown in Figures 7 and 8. The red marks in show the level of congestion. In these figures, links with flow/capacity ratio less than 0.8 are shown in green, links with flow/capacity ratio greater than or equal to 0.8 but less than 1 are shown in yellow, and links with flow/capacity ratio equal to 1 or greater are shown in red.

Ideal Flow Network Analysis

Figures 9, 10, 11, and 12 shows the results of the IFN analysis. As before, green links correspond to flow/capacity ratios that are greater than or equal to 1, yellow links correspond to flow/capacity ratios that are between 0.8 and 1, and red links correspond to flow/capacity ratios that are less than 0.8. The red links are those links that are potentially congested. Results shown in Figures 9 and 10 were derived using the stochastic matrix being guided by the OD of the TA. Figures 11 and 12 were derived using the stochastic matrix based on the link capacities.

Table 2 shows the different level-of-service (LOS) values for urban streets. The LOS is a scaling of the speed in comparison to the free flow speed. Speed, in turn, is a scaling of the flow/capacity ratio. This means that the LOS is another way of visualizing the preceding figures.

Traffic Assignment *vs*. Ideal Flow Network

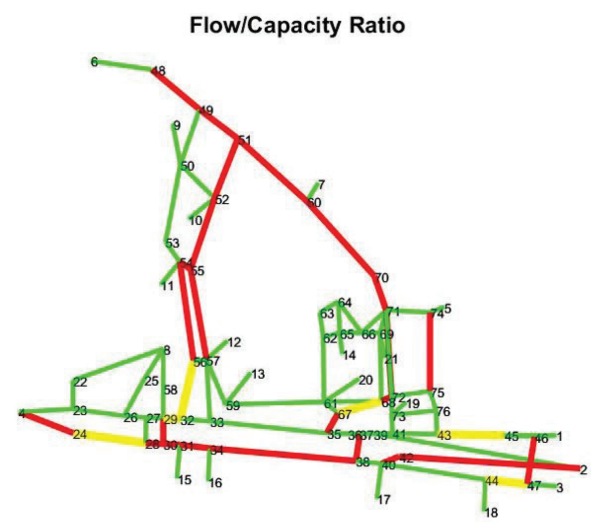


Figure 7. Flow/capacity ratio using TA, two-way (base scenario).

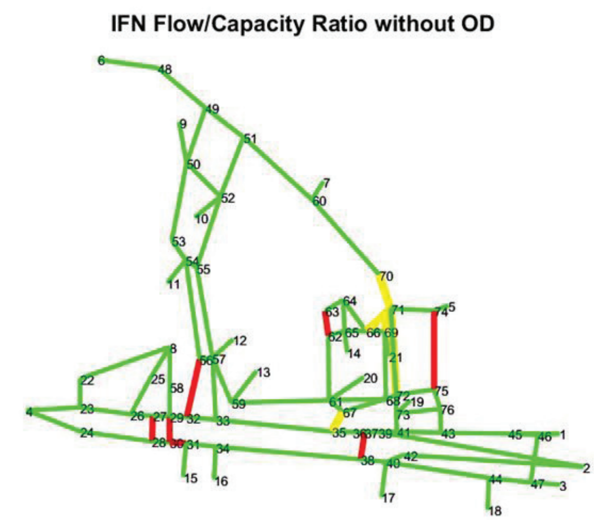


Figure 9. Flow/capacity ratio using IFN without OD, two-way.

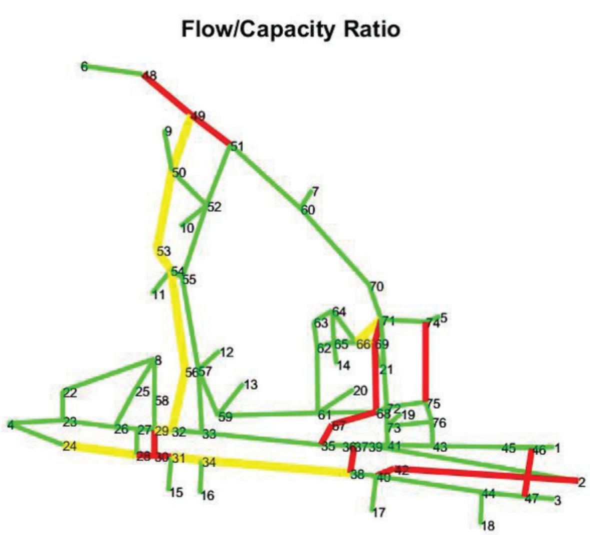


Figure 8. Flow/capacity ratio using TA, one-way.

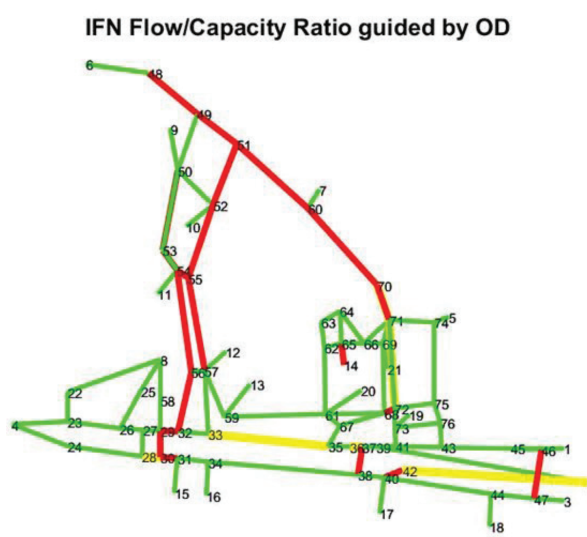


Figure 10. Flow/capacity ratio using IFN with OD, two-way.

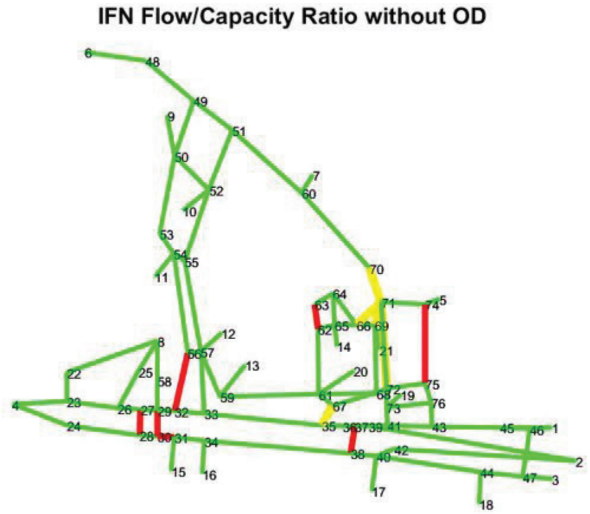


Figure 11. Flow/capacity ratio using IFN without OD, one-way.

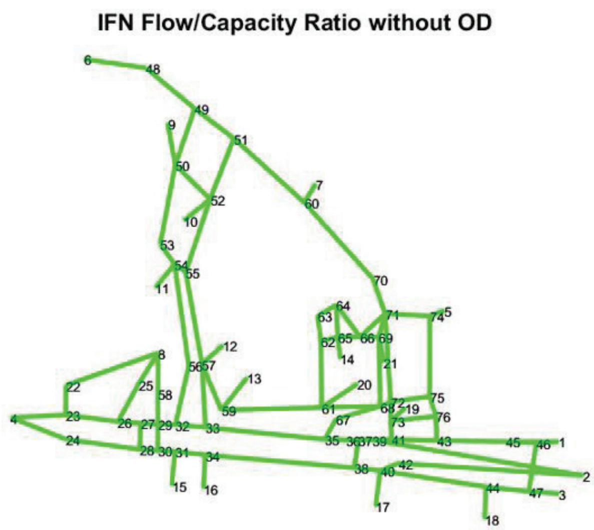


Figure 12. Flow/capacity ratio using IFN without OD, one-way.

Figures 13 and 14 show comparison of flow frequencies between $\mathbf{F}_a$ and $\mathbf{F}_b$, $\mathbf{F}_a$ and $\mathbf{F}_c$, and $\mathbf{F}_b$ and $\mathbf{F}_c$. Figure 13 shows how close the results of TA are against those derived using IFN guided by the OD. The results shown in Figure 14, on the other hand, are close in the earlier portions of their graphs; however, as the flow increases, the tail of the TA results are longer.

Table 2. LOS (NRC 2010).

LOS	Travel speed as a percentage of base free flow speed
A	>85
B	>67–85
C	>50–67
D	>40–50
E	>30–40
F	<30

For people who have local knowledge, introducing a change in the traffic supply has produced quite an amazing

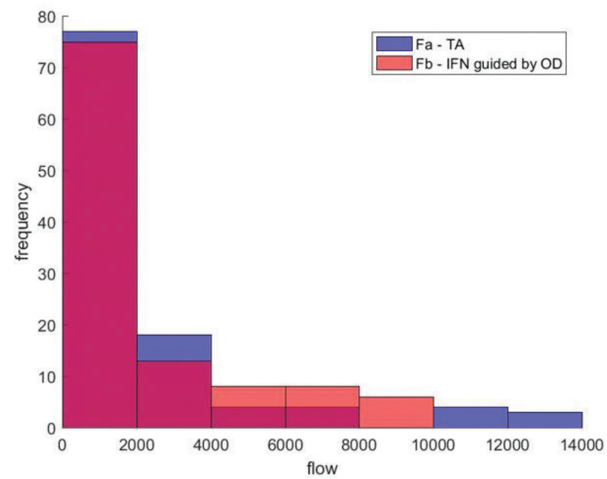


Figure 13. TA vs IFN guided by OD.

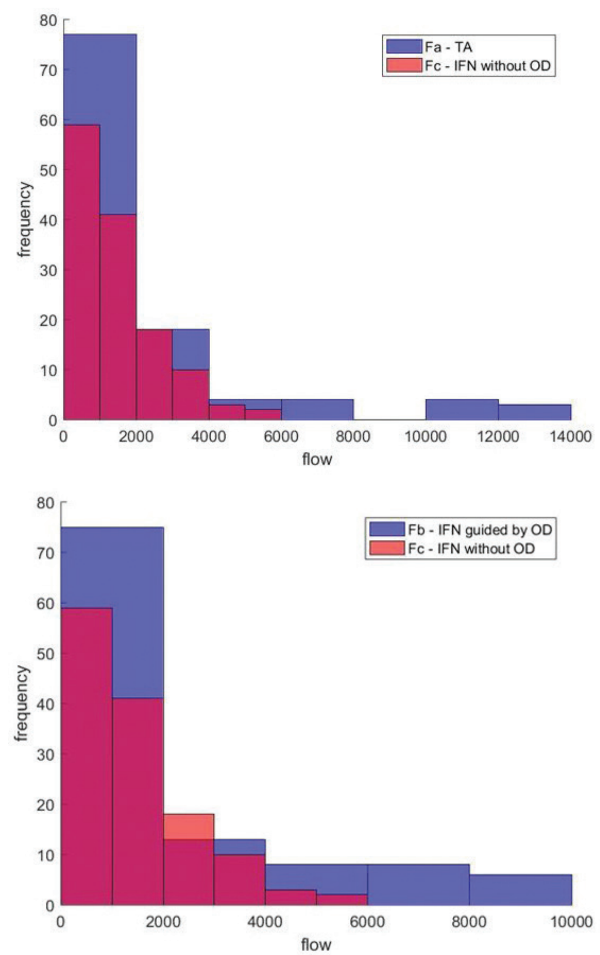


Figure 14. IFN without OD *vs*. TA (left) and *vs*. IFN guided by OD (right).

result. The one-way traffic scheme affected the congested links. Indeed, the notion that physical infrastructure can (re)configure practices has been illuminated in various studies. For example, Saloma and Akpedonu (2016) describe how the material dimension influence food consumption practices in vertical neighborhoods. In the dynamics of escape panic, self-organized queuing could be induced by exit size (Saloma *et al.* 2003). From an analysis of accidents and crashes, Shinar (2017) demonstrates how efforts toward vehicular and environmental changes, instead of punishment, are more effective in eliminating crash-causing behaviors or mitigating their effects.

SUMMARY OF RESULTS

Table 3 shows the network speed comparison among TA, IFN guided by OD, and IFN based on network structure alone. The TA result and the IFN guided by OD result are consistent – when the two-way structure was changed to a one-way structure, the network speed increased. This implies that when comparing scenarios, the correct stochastic matrix (as guided by OD) will give consistent results. However, the IFN model based on structure alone may reverse the result, as shown in the third row. This is a limitation of inferencing without data. This means that better data will produce better results, as expected.

Table 4 contains norm comparison. The value of $\mathbf{F}_a$ is closest to $\mathbf{F}_b$. This strongly suggests that the OD can be replaced by stochastic matrix. If the right stochastic matrix is known, the OD data is not a necessity anymore. A stochastic matrix is not necessarily obtained from a TA model. It can also be obtained from real world data, such as those from intelligent transportation systems through cameras or GPS tracking.

Table 3. Speed comparison (kph).

Model	Two-way (Base)	One-way
TA	13.90	15.83
IFN guided by OD	23.44	26.32
IFN without OD	55.15	51.99

Table 5 shows comparison among R-squared values. These values help to check correctness of results. The network structure can be used to estimate flow but may not be precise because the error can be very large, as can be seen by the negative R-squared value in the last column. A negative R-square means that the sum of squares error (SSE) is larger than the squared mean differences.

Table 4. Norm comparison.

Norm	Two-way (Based)	One-way
$\|\|\mathbf{F}_b(\kappa_b^*) - \mathbf{F}_a\|\|$	9,003.32	4,228.56
$\|\|\mathbf{F}_c(\kappa_c^*) - \mathbf{F}_a\|\|$	11,583.93	12,220.44
$\|\|\mathbf{F}_c(\kappa_c^*) - \mathbf{F}_b(\kappa_b^*)\|\|$	8,661.46	9,477.63

Table 5. R-squared comparison.

	Two-way (Based)	One-way
$R^2\ to\ \min_{\kappa}\|\|\mathbf{F}_b(\kappa) - \mathbf{F}_a\|\|$	0.632	0.808
$R^2 to\ \min_{\kappa}\|\|\mathbf{F}_c(\kappa) - \mathbf{F}_a\|\|$	0.1007	–0.4416

CONCLUSION

In this paper, a traditional TA model and the IFN model were used to analyze a campus network with the goal of addressing information scarcity on traveler behavior. In comparing these two models, a generic model comparison concept was proposed. Results show that the IFN model's estimation of the current flow is close to the results of the traditional TA guided by the OD matrix. The IFN model, however, has an advantage over traditional traffic assignment models in that it can simply use a stochastic matrix that can be obtained from different sources – such as camera systems, GPS tracking, or fiber optics – other than the OD matrix in order to make a good enough estimate of the current traffic flow, as presented here in a case study. It, therefore, reduces the attendant financial costs of data generation. Moreover, it lessens the social costs of introducing change since the model can identify "what works" and find how the proposed intervention can adapt to new challenges prior to implementation in the real world. As a future work, this model can also produce a measure of how efficiently utilized are any given existing road network in contexts such as university campuses and megacities. With that information, traffic planners can see how far is the current structure from the ideal, and thus be able to plan on how to make improvements such as building roads in correct locations or the deliberate destruction of some to alleviate congestion. This study, thus, has implications for traffic management decision making as it emphasizes the importance of understanding how the material dimension of traffic supply – such as the road network structure – can generate evidence for traffic flows. The calibration of the road network based on transportation supply information to limit the cost of the search for traveler behavior information is a practical outcome of the overall structure of the IFN model and an element within that model. The precision of the IFN model would increase depending on the completeness of the input information. The calibration of the ideal flow based on parsimony data of travel demand will be discussed in another paper.

ACKNOWLEDGMENT

This study is supported by the Institute of Philippine Culture and the Commission on Higher Education (Philippine Higher Education Research Network and the K to 12 Scholarship). The authors also acknowledge with gratitude the Ateneo Traffic Group.

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