Lab 4: Traffic Stream Models

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ABSTRACT

The field data from loop detectors on US 290 EB (freeway) at Woodbury Drive in Austin, Texas was used in the lab. The data set was composed of volume, flow rate, occupancy, speed, and number of trucks during the 10 months. Traffic stream models were developed related to the speed and density, flow rate and density, speed, and flow rate. The variables were plotted against each other and an analysis done on the results. A multi-regime model was found to be the most appropriate for fitting the dataset. The breaking points of the models were decided by detection of where the trends tended to change. The coefficients of determination value are used to measure how well the models fit the data. By analysis, relatively high R-square values of the models were achieved.

Key words: Multi-regime model, traffic stream models

INTRODUCTION

Traffic stream models provide the fundamental relationships of macroscopic traffic stream characteristics for uninterrupted flow situations. Traffic stream models describe the relationships among traffic variables. With the knowledge of traffic characteristics, we can use the models to predict traffic flow performance. Examples of common models are Greenshields' Model, Greensberg's Model, Underwood's Model, and multi-regime models among others.

In this laboratory exercise, the data used was collected by loops in 2004 at US 290 EB close to Woodbury Drive in Austin, Texas. The relationships of flow rate, speed and density were determined based on the data. The location is shown below:

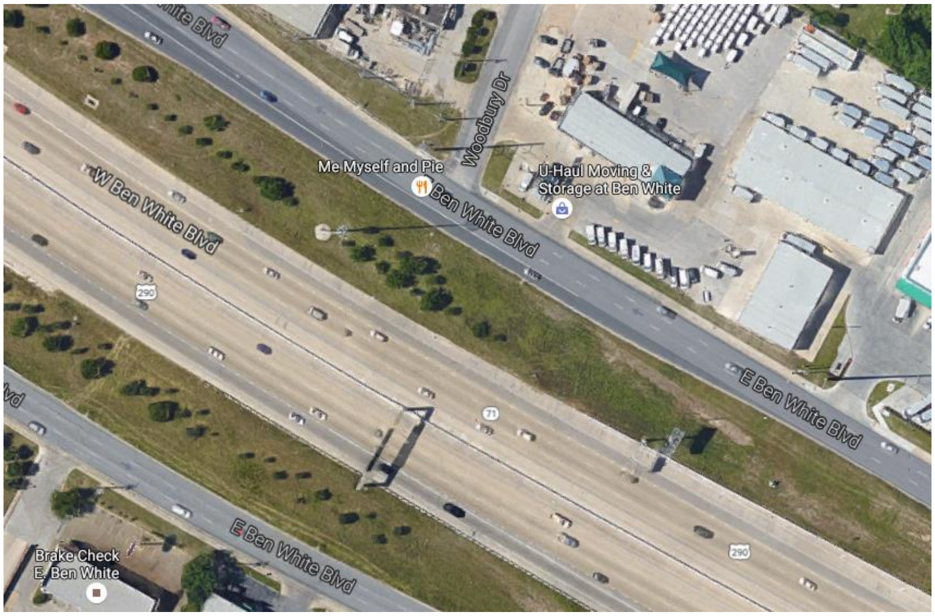

FIGURE 1 Location of Study

OBJECTIVES OF THE STUDY

Get acquainted with the process of developing traffic stream models using real-world data.

LITERATURE REVIEW

Traffic Stream Models: Single-Regime Models

The first single-regime model was developed by Greenshields in 1934 based on observing speed-density measurements obtained from an aerial photographic study (1). The model requires knowledge of the free-flow speed and jam density parameters in order to solve numerically for the speed-density relationship.

$$u = u_f - \frac{u_f}{k_j} k$$

The Greenberg model was another single-regime model that was proposed (2). Observing speed-density data sets for tunnels, with particular attention to the congested portion, he concluded that a nonlinear model might be more appropriate. One of the important results of Greenberg's work was the bridge that was discovered between his proposed macroscopic model and the third General Motors car-following model.

$$u = u_0 ln(\frac{k_j}{k})$$

The third single-regime model was proposed by Underwood as a result of traffic studies on the Merritt Parkway in Connecticut (3). Underwood was particularly interested in the free-flow regime and was disturbed by free-flow speed going to infinity in the Greenberg model.

$$u = u_f e^{-k/k_0}$$

Edie first proposed the idea of two-regime models in 1961 because of reservations of using car-following based models under free-flow conditions and his observation of the poor performance of the Greenberg model under free-flow conditions (4). More specifically, Edie proposed the use of the Underwood model for the free-flow regime and the Greenberg model for the congested-flow regime. The multi-regime models provide a considerable improvement over single-regime models.

Multi-Regime Model	Free-Flow Regime	Transitional Flow Regime	Congested-Flow Regime
Edie model	$u=54.9e^{-k/163.9}$ $(k \le 50)$	-	$u=26.8ln(\frac{162.5}{k})$ $(k \ge 50)$
Two-regime model	$u=60.9-0.515k$ $(k \le 65)$	-	$u=40-0.265k$ $(k \ge 65)$
Modified Greenberg model	$u=48$ $(k \le 35)$	-	$u=32ln(\frac{145.5}{k})$ $(k \ge 35)$
Three-regime linear model	$u=50-0.098k$ $(k \le 40)$	$u=81.4-0.913k$ $(40 \le k \le 65)$	$u=40-0.265k$ $(k \ge 65)$

Source: Drake and Schofer, 1967 (5).

Traffic Stream Models: Multi-Regime Models

Road traffic assessment models depend mainly on the cornerstone mathematical relationship between speed and flow. Recently, there have arisen models that have been developed for simulation such as car-following models and lane changing models. However, these models need to be calibrated before being applied in evaluation, design and planning, where traffic stream models are needed.

Al-Jameel and Al-Jumailli (6) developed such relationships both on microscopic and macroscopic levels between speed, flow, occupancy, density, and headway based on the 1 minute loop data (3 lanes) and 1 second data (4 lanes) provided by the Motorway Incident Detection and Automated Signaling (MIDAS) system. It was found that the speed-flow relationship followed Greenshields' model. Additionally, the variation of vehicle speed changes between lanes with the outside lane having the highest variation in speed and the inside lane having the lowest variation in speed. As for the flow-occupancy relationship, the range of values for critical occupancy according to site conditions was found to be 19% to 25%. For the flow-headway relationship, the field data suggested a negative correlation which can be represented by a set of regression equations corresponding to each lane scenario and each lane that had similar behavior. The flow-density relationship was found to follow Greenshields' model as well. The optimal density was close to the values in the 2000 Highway Capacity Manual (HCM) and HCM 2010 for basic freeway segments using 5 minute calculations instead of 1 minute calculations.

Xie et al. (7) proposed and tested a generic link speed estimation model based on loop detector data and traffic signal timing parameters as inputs which didn't require a calibration process in model forming. The model was listed as follows:

Travel time = cruise time + signal delay, where:

$$Cruise\ time = \frac{L_1}{u_{det}}$$

$$Signal\ delay = 0.9\phi\left[\frac{C(1-\lambda)^2}{2(1-\lambda x)} + \frac{x^2}{2q(1-x)}\right]$$

u_{det} is maximum speed of the upstream and downstream detector stations.

λ is the effective green proportion (g/C)

L_1 represents intersection geometry

C is cycle length

ϕ is calculated parameter

There are some studies that are associated with the calibration of model parameters. According to Rakha and Arafeh (8), most existing traffic flow theories and models were built under the assumption of the existence of a specific unique relationship between traffic stream variables (flow, speed, density, etc.). In this case, their study presented a bi-level optimization approach for calibrating traffic stream models that didn't require variable dependence, which combined the Van Aerde traffic stream and car-following models. It was found that the associated autocalibration tool (SPD_CAL solver) performed better than the MINOS and BARON solvers both in terms of execution time, computational efficiency and algorithm robustness.

Sun et al. (9) presented a new multi-regime traffic stream model that applied B-spline regression theory to existing traffic flow theory. By increasing the number of regimes, a multi-regime traffic stream model becomes capable of more accurately depicting the complete gradient of traffic operation conditions. However, a large number of regimes are associated with low computation efficiency and high model complexity, both of which make the multi-regime traffic stream model inconvenient to use. The B-spline function in this case is used as a tool to organize the multiple regimes and smooth the transitions between them. The study found a five-regime B-spline model corresponding to five traffic operating conditions: free flow, transition, synchronized flow, stop and go traffic, and jam conditions

Freeway Monitoring and Data Collection

As early as the period directly following World War I, interstate highways were being built in the United States. To aid in planning and design activities, traffic data would need to be collected. In the early years technology was limited and there were a few ways of collecting highway data. One way of collecting traffic data from highways would be the use of the pneumatic road tube which was invented in the 1920s. While it is a relatively simple tool compared to some modern techniques, the pneumatic tube is still in use today because of its ease-of-use and its usefulness in providing traffic data such as vehicle length and speed.

Other ways of obtaining traffic and driver behavior data from highways include surveying drivers directly and collecting data manually through techniques such as traffic counts. However, both of these techniques are very labor-intensive and thus quite costly while yielding relatively inaccurate results compared to what can be obtained from more modern methods.

As the interstate highway system begin to see more and more use over time it also became necessary to use improved methods of data collection in order to obtain more accurate results and to be able to better describe not only traffic conditions but also the vehicles using the highway facilities.

Sensors are a popular way to collect highway data passively without the need of a constant human observer. One class of highway sensors is in-pavement sensors. Initial installation costs may be high due to the need to break the pavement and install the sensor, but once the in-pavement sensor is installed it can continuously feed data to the researcher. Specific types of in-pavement sensors include capacitance pads, load cells, strain gauges, and piezoelectric sensors (10). The data set used in this laboratory exercise comes from data obtained from in-pavement induction loop sensors.

Other technologies for data collection are less intrusive, not requiring installation of a sensor into the pavement. Not having to install sensors into the pavement reduces cost of installation. Less intrusive data collection methods also increase safety and reduce traffic problems that may have been associated with having to close down portions of a facility in order to install and maintain the sensors. These technologies include video, infrared, laser, radar, and other types of detectors that collect data from a distance (10). These technologies also tend to be more mobile and thus can be used at different locations as needed.

One of the most promising, currently developing resources for freeway monitoring and data collection is passively contributed "floating car" position data. While the specific mechanisms may differ between different technologies the concept tends to be the same: collect data from a transmitter located in the vehicle or on the driver and receive the data at fixed collection points along the roadway or via satellite. The technologies that fall under this category include RFID tags, GPS or global positioning system methods, Bluetooth, and smartphone-based data. Having real-time and accurate data on actual vehicles using a highway facility greatly improves the ability to understand traffic flows, model them appropriately, and respond to problems such as congestion and accidents in a more efficient manner. The concept of obtaining a more complete picture of real-time traffic conditions on a microscopic level is called achieving ground truth, a term reflecting the promising nature of this continually improving technology (11).

The most promising and exciting method of highway traffic monitoring and data collection may yet lie in the near future. Automated and connected vehicles, while still in the developmental phase, have the potential to share information with a connected roadway network and exponentially increase the amount of data that we are able to obtain while still maintaining an extremely high level of data accuracy. While reliability and cost issues still must be solved, the vast amounts of accurate and real-time data from these systems have the ability to enable researchers to develop more accurate models, to better understand traffic, to make more accurate predictions, to design facilities more efficiently, and to improve the overall experience of the driver on the road (12).

In the end, since most analysis and use of collected data is done on computing systems and these computing systems are dependent on the way in which they are programmed, increasing the accuracy of data leads to greater accuracy in modeling, which in turn leads to better data analysis.

LAB METHODOLOGY

In traffic stream theory, flow rate is equivalent to speed multiplied by density. Using the data introduced above, traffic stream models were developed based on the flow, volume, speed and density. Several models were developed for the relationships between flow and density, speed and flow, speed and density. Scatterplots were made for the variables.

According to the different trends in the plots, breaking points were decided to separate the model into multiple regimes. To test how well the models fit the data, the R-squared value (coefficient of determination) was calculated.

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$$

$$SS_{tot} = \sum_{i} (y_i - \bar{y})^2$$

$$SS_{res} = \sum_{i} (y_i - f_i)^2$$

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

In these formulas, y_i is the observed data, y is the mean value, and f_i is the predicted data. The R^2 value ranges from 0 to 1. The closer the R^2 is to 1, the more accurately the model fits the data. Before the analysis of the data, 24 outliers and singular values were deleted.

Speed vs. Density

The speed-density relationship is one of the basic relationships among macroscopic traffic stream variables. The data scatterplot of speed versus density for the data set is shown in the graph below:

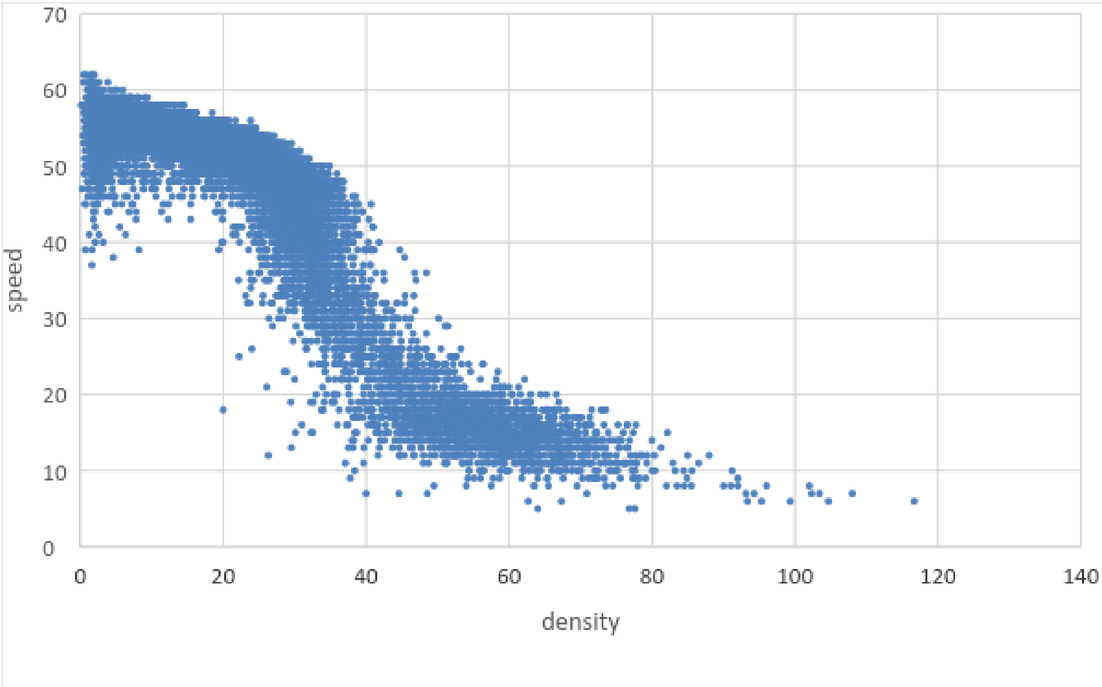

FIGURE 2 Speed vs. Density Scatterplot

It can be seen from the scatterplot that the relationship between speed and density can be divided into three scenarios corresponding to the free flow scenario, intermediate scenario, and congestion scenario. Under the free flow condition, the speed-density relationship is close to what suggested by HCM 2010. In other words, the elasticity of speed in response to changes in density is low due to the overall low volume on the facility. In this case, the speed density relationship can be viewed as constant, which is represented by a flat line model.

According to the scatterplot and level of service, we assume two thresholds of density to be 25 vehicles per minute (vpm) and 40 vpm. When density is less than 25 vpm, the traffic flow is almost free flow. When density is between 25 vpm and 40 vpm, the traffic is intermediate flow. When density is larger than 40 vpm, the traffic situation is fully interacting. Based on traffic data, when k is 25 vpm, the average speed is 53 mph. And when k=40 vpm, the average speed is 23 mph.

From these calculations we can see that the first part of the speed-density plot can be described as:

$$v = 53 \text{ mph (where } 0<k\leq 25)$$

This condition changes when density is approximately 25 vpm, where the vehicles are not as unstable as under the free flow situation and the speed is no longer constant. From the observations, the speed-density relationship is almost linear. Thus for the second part, the Greenshield's model is applied, resulting in the following formula:

$$v = -2k + 103 \text{ (where } 25<k\leq 40)$$

When it comes to the congestion scenario, the speed-density relationship is no longer linear. Judging from the scatterplot, when the density is above 40 vpm, the curve representing this relationship is concave. Based on the formulas, Greensburg's model shows high reliability for high density condition compared with other models such as Greenshields' and Underwood's. Therefore it is selected to represent the congestion scenario. After discussion, the researchers choose a point to calibrate the Greensburg's model. When k=40 vpm, average speed is 23 mph, and when k=75 vpm, the average speed is 13mph. Thus the parameters in this model can be calibrated. The model is shown in the following equation:

$$v = 15.9 \ln \frac{170}{k} \text{ (where } k>40)$$

Overall, the speed vs. density model can be written as:

$$\begin{cases} v = 53 & 0 < k \leq 25 \\ v = -2k + 103 & 25 < k \leq 40 \\ v = 15.9 ln \dfrac{170}{k} & 40 < k < 170 \end{cases}$$

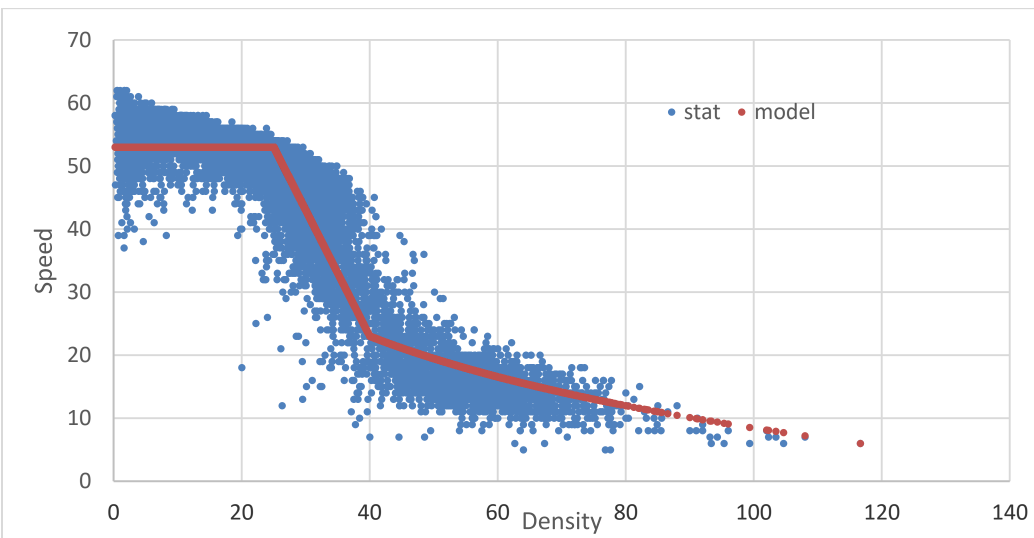

FIGURE 3 Speed-Density Model

Flow vs. Density

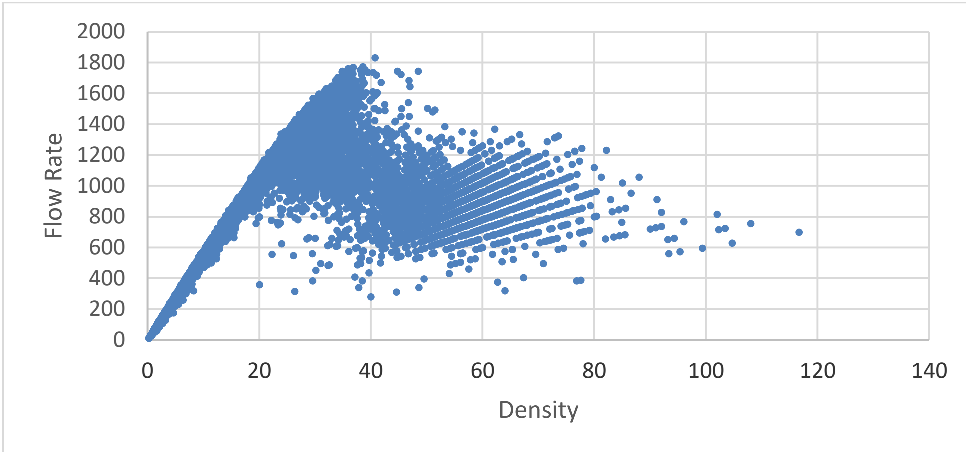

FIGURE 4 Flow Rate vs. Density Scatterplot

It is apparent from the flow rate-density scatterplot that the relationship between flow rate and density is difficult to describe when density is larger than 25 vpm. However, for density levels less than 25 vpm, the flow rate is almost linearly related to density. This finding is consistent with the previous suggestion that speed is constant when density is less than 25 vpm.

In traffic stream theory, flow rate is equal to speed multiplied by density. Since we have established the speed-density relationship, we can also easily obtain the flow rate-density relationship:

$$\begin{cases} q = 53k & 0 < k \ll 25 \\ q = -2k^2 + 103k & 25 < k \ll 40 \\ q = 15.9k ln\dfrac{170}{k} & 40 < k < 170 \end{cases}$$

The function can be plotted as the red line in the flow rate-density scatterplot as follows:

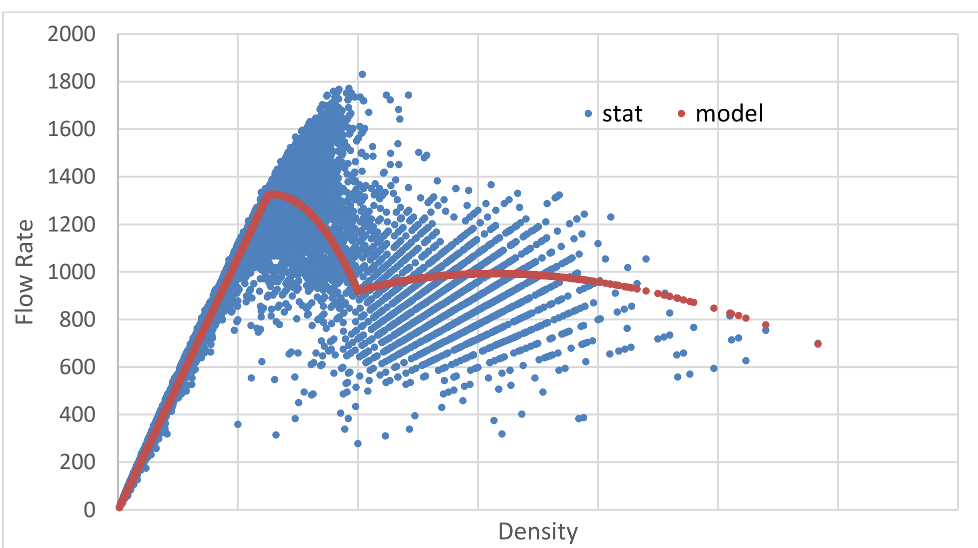

FIGURE 5 Flow Rate-Density Model

Speed vs. Flow Rate

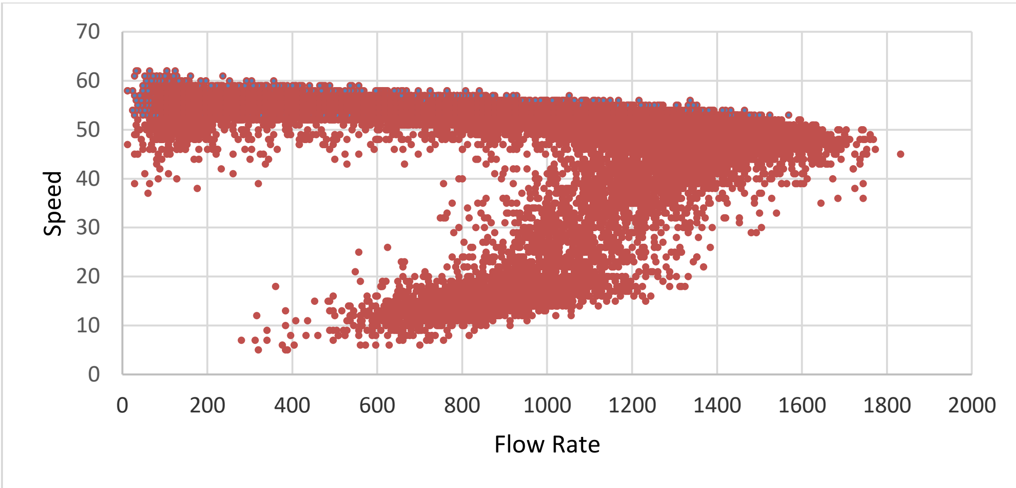

FIGURE 6 Speed vs. Flow Rate Scatterplot

As we can see from the speed-flow rate scatterplot diagram, the scatterplot can be separated into three parts as previously described. The first part is the free flow situation in which speed is nearly constant. When the traffic flow becomes stable, the speed goes down.

Following the v-k function, the speed flow rate relationship can also be derived:

$$\begin{cases} v = 53 & v > 53 \\ q = -0.5v^2 + 51.5v & 23 < v \ll 53 \\ q = 170v/e^{v/15.9} & v \ll 23 \end{cases}$$

The function can be plotted in the flow rate-density scatterplot as follows:

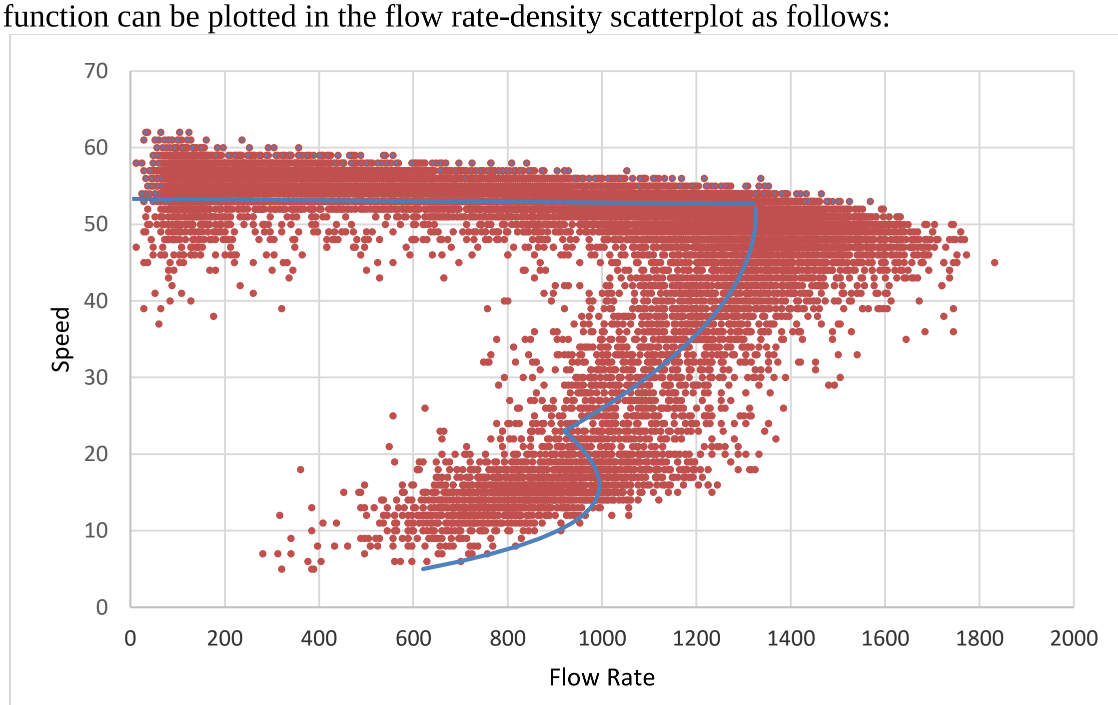

FIGURE 7 Speed-Flow Rate Model

Goodness-of-Fit Test

The R-squared goodness-of-fit test was used to evaluate the appropriateness of the proposed models in relation to the given data.

For the density-speed traffic stream model, the mean of observed data is:

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i = 49$$

Then the variability of the data set can be measured using three sums of squares formulas:

The total sum of squares:

$$SS_{tot} = \sum_i (y_i - \bar{y})^2 = 3221098$$

The model sum of the squares, also called the explained sum of squares:

$$SS_{model} = \sum_i (f_i - \bar{y})^2 = 2840201$$

The sum of the squares of residuals, also called the sum of error:

$$SS_{res} = \sum_i (y_i - f_i)^2 = 353304$$

The most general definition of the coefficient of determination is:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 0.89032$$

The density-flow rate and flow rate-speed models were tested using the same procedure as described above. The results are shown in the table below:

TABLE 1 R-Squared Results for Each Proposed Model

Model	SS_{model}	SS_{res}	R^2
Speed-Density	2840201	353304	0.89032
Flow-Density	5853809280	303418785	0.94817
Flow-Speed	20248702014	1147354259	0.943337

The R-squares calculated are relatively close to 1, which is good indicator that the proposed models are a good fit to the data. From the values it can be concluded that about 90% of the change in each variable can be explained by the model.

Occupancy vs. Density, Speed and Flow Rate

The data provides field measured occupancy instead of density. Theoretically, occupancy can be converted into density using the following formula which is provided in May's book (13):

$$k = \frac{52.8}{L_V + L_D}(\%\ occ)$$

L_V is the average vehicle length and L_D is the length of the loop detector. However, according to the observed data, occupancy is not exactly linearly related to density, especially when both occupancy and density are large, which is shown in the following scatterplot:

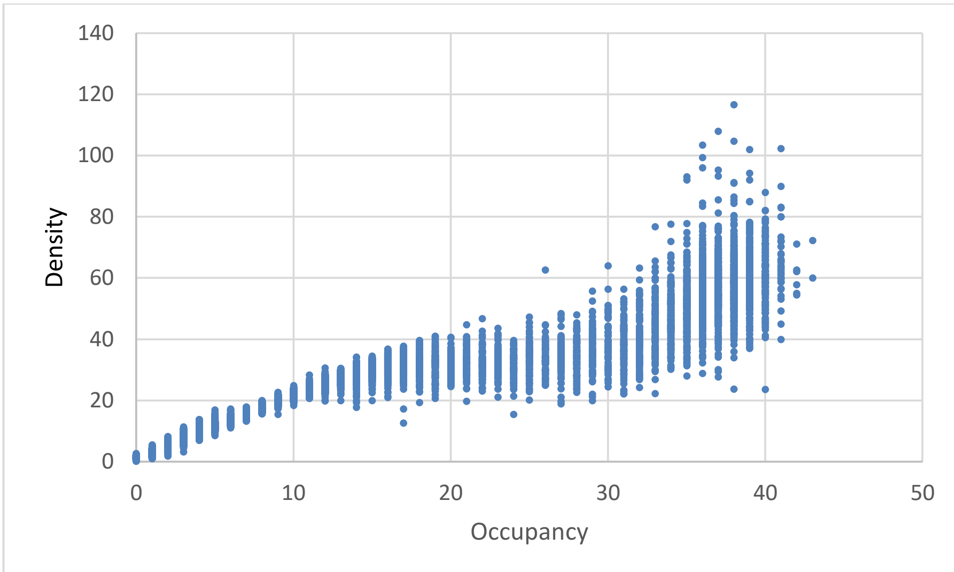

FIGURE 8 Occupancy vs. Density Scatterplot

From the scatterplot diagram, density is approximately linear to occupancy only when both of them are small. As a result, it is unreliable to predict this relationship simply using a straight line model.

The following diagrams are the speed-occupancy scatterplot diagram and the flow rate-occupancy scatterplot diagram respectively. It can be observed that occupancy has a clearer mathematical relationship with speed and flow rate than density.

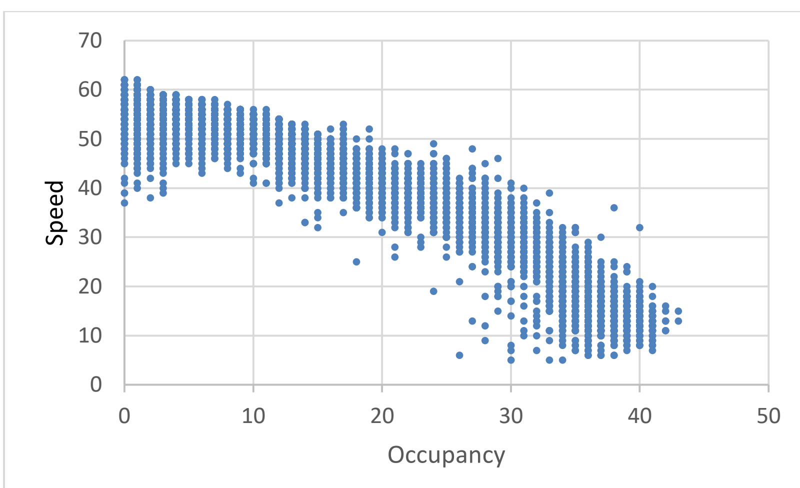

FIGURE 9 Speed vs. Occupancy Scatterplot

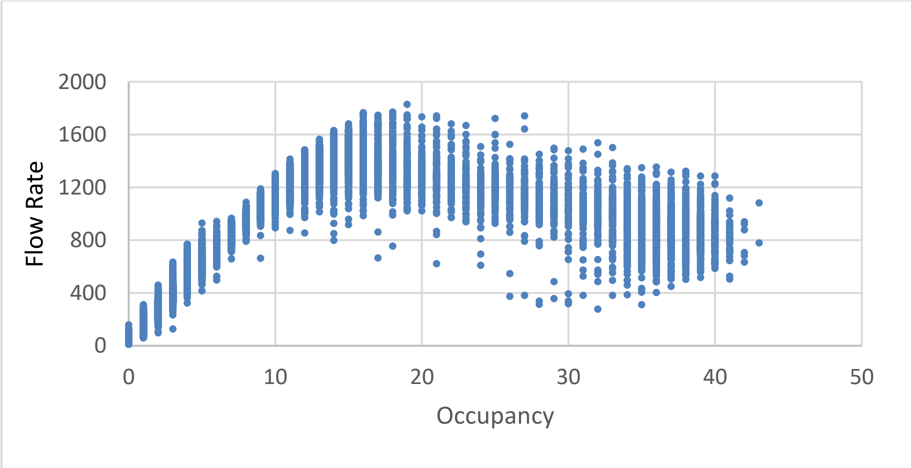

FIGURE 10 Flow Rate vs. Occupancy Scatterplot

The scatterplots of occupancy vs. speed or flow rate are more likely to align with the classic traffic stream model used in HCM 2010 in which density is used instead of occupancy. As the relationships illustrated by the data in the scatterplots is hard to predict, no clear numerical relationship of occupancy vs. speed is proposed in this report, so does the relationship of occupancy vs. density and occupancy vs. flow rate.

DISCUSSION

The data used in this laboratory experiment shows an inconsistent relationship between occupancy and density when occupancy is over 30%. If more data were available, this relationship may be made clearer to define. One possible reason for the inconsistent relationship between the variables is that as density increases, vehicles in the traffic stream begin to interact with one other. Under such a circumstance, the traffic stream model is no longer purely macroscopic. Microscopic models such as lane changing models and car-following models need to also be taken into consideration. An appropriate model would not only need to be multi-regime, but it would also need to be multi-scope. If this additional data were made available, a more complex model could be formed taking into account microscopic factors. Loop data at shorter intervals than the given 15 minutes may also be needed to better serve the microscopic models. As long as the relationship between occupancy and density can be determined, the relationship of flow rate vs. occupancy and speed vs. occupancy can be determined as well.

Additionally, one way in which the analysis could potentially be expanded is to include more than 2 variables in the calculated model. While it is simpler to judge, calculate, and understand, the traffic stream model does not need to be a traditional 2-D model with 2 variables. A 3-D model can include three variables at the same time. Also, other variables can be included in the model in addition to the basic variables (density, speed and flow rate). For example, models can be built based on travel time vs. density. While these opportunities for extension carry great interest, limitations of the dataset preclude their inclusion in this laboratory experiment.

CONCLUSION

In this lab report, the relationship between macroscopic traffic stream variables was examined as applied to 15-minute loop data. It was found that a single model like Greenshield’s model or Greensburg’s model alone is not sufficient to completely and accurately describe the relationship between traffic stream variables. This report proposed a multi-regime model with three scenarios: the free flow scenario, the intermediate scenario, and the congestion scenario. This model was established using data from the speed-density relationship. From that basis, the flow-speed and flow-density relationships were added to the model.

While density values used to calibrate the model were not directly provided by the field measured data, what the data provides is occupancy. It is found that occupancy is not in an entirely straight linear relationship with density as suggested in May's book (13). Therefore, the speed-occupancy relationship and flow rate-occupancy relationship cannot be determined, even though at certain values, they may appear to follow the mathematical relationship described in the Highway Capacity Manual.

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Participation Form: 100%

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