ESTIMATING VEHICLE MILES OF TRAVEL ON LOW FUNCTIONAL CLASSES OF ROADWAYS

A Thesis

by

XIAOWEI CAO

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Chair of Committee,	Xiubin Bruce Wang
Committee Members,	Mark W. Burris
	William L. Eisele
Head of Department,	Robin L. Autenrieth

December 2015

Major Subject: Civil Engineering

ABSTRACT

In this research, new methods to estimate vehicle miles traveled (VMT) for lower functional classes of roadways are introduced. The methods are based on the inherent correlation between VMT and roadway densities in each roadway class. This research found that the relationship between VMTs of different functional classes of roadways has to do with roadway typological structures according to functional classifications. To begin with, the analytical relationship between local VMT and collector road VMT was derived by assuming a grid network. The purpose was to find key relevant terms (basically roadway densities) in the relationship, which were used to define the format of regression equations. Next, the author proposed two types of regression models, one using density ratios as explanatory variables and the other using logarithmic value of roadway densities. Several simulation networks were set up to verify those proposed models using community road patterns categorized according to three different measures. The author found that the proposed models worked well for medium and high connectivity networks, but they were inadequate for simulating low connectivity networks. Moreover, the equation using logarithmic terms provided a better result in every numerical test. Next, the author verified the proposed regression equations in real situations. The results showed that the proposed regression models work very well in estimating urban local VMT of Minneapolis (grid networks). However, the relative error was much bigger in estimating local VMT of Bryan/College Station (non-grid networks). Finally, the author introduced a practical application procedure and also discussed the possible sources of errors in this study. This research introduces a potentially more efficient method (logarithm) for estimating VMT for lower functional classes of roadways.

DEDICATION

I dedicate this thesis to my parents, Weiming Cao and Jingying Liu, for their consistent love in my life.

ACKNOWLEDGEMENTS

I would first like to thank my advisor, Dr. Bruce Wang for his guidance and support of my research.

I would also like to thank Dr. Burris and Dr. Eisele for serving on my committee and for their comments.

I am especially grateful for Jiayu's help throughout this research project. I also would like to thank my graduate fellows Wen Wang and Lisa Zhong for their valuable advice during my master's study, which benefited me greatly.

NOMENCLATURE

d	spacing between local roads
L	spacing between collector roads
D	spacing between minor arterial roads
S	spacing between principal arterial roads
VMT_L	local road VMT
VMT_C	collector road VMT
VMT_{MA}	minor arterial road VMT
t_{local}	average local distance traveled
$t_{arterial}$	average principal arterial road distance traveled
ρ_1	local road density
ρ_2	collector road density
ρ_3	minor arterial road density
ρ_4	principal arterial road density

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

TABLE Page

1. INTRODUCTION

Vehicle miles traveled (VMT) refers to the total miles traveled by vehicles on roadway. Every year, state departments of transportation (DOT) nationwide report the VMT on all functional classes of roadways, both in urban and rural areas to the United States Department of Transportation. VMT is often used for transportation design, planning, decision making, federal fund allocation, air quality control, and traffic accident analysis. The Internal Revenue Service (IRS) collects the federal fuel excise tax (taxes paid when purchases are made on fuel or gasoline) to deposit in the Highway Trust Fund (HTF) [1]. At least 91% of the federal fuel tax goes back to states. Federal legislation requires generally that funds paid into the HTF be returned to the states for various highway program areas in accordance with legislatively established formulas [2]. These formulas use fuel and other excise taxes attributed to each state as distribution factors, which are forecast mainly by VMT as well as fuel efficiency of vehicles. Therefore, it is important for states to obtain accurate VMT data on functional classes of roadways, and there are various ways to estimate the VMT numbers.

Table 1.1 shows the specific classifications of federal-aid (upper functional classes) and non-Federal-aid systems (lower functional classes).

According to Highway Performance Monitoring System (HPMS) Field Manual [3], estimates of Daily Vehicle Miles of Travel (DVMT) are developed by direct computation for all federal-aid Highway functional systems. This is generated by the HPMS software which multiplies the section annual average daily traffic (AADT) by the section length and sums the result to the HPMS aggregation level desired (functional system, total rural, etc.). Such AADT data are developed based on the

Table 1.1: Highway Functional System Classifications. (*Source*: HPMS Field Manual, 2014 [3])

RURAL	
Federal-Aid	**Non-Federal-Aid**
Interstate and Non-Interstate	Minor Collector
Other Freeways, Expressways and Principal Arterials	Local
Minor Arterial	
Major Collector	
URBAN	
Federal-Aid	**Non-Federal-Aid**
Interstate and Non-Interstate	Local
Other Freeways, Expressways and Principal Arterials	
Minor Arterial	
Major Collector	
Minor Arterial	

traffic counts collected by a State Traffic Data Program for HPMS.

Automatic traffic recorders (ATRs) provide continuous monitoring of existing traffic conditions around the state. Travel on freeways, expressways and other multilane facilities can be monitored by route. Travel can also be monitored by area through statewide or MPO freeway management or travel surveillance programs, such as Intelligent Transportation System (ITS) deployments. Other highway functional systems, both State and off-State, can be monitored by geographic area, such as by county or highway district. Traffic information in a comprehensive count program should be compiled from all available sources – MPO, ITS, state, city, and county.

For estimating VMT on non-Federal-aid highways (local or minor collector roads), various methods are used by different states. Some examples of good state practices are providing:

- Current traffic growth rate on collectors or higher systems;

- Limited samples of short term traffic counts;
- Combination of sample and estimated counts; and
- Area-wide average count daily traffic based on documented methods.

The monthly Traffic Volume Trends report is published by the Federal Highway Administration (FHWA) based on a sample of traffic data from state ATRs. Annual VMT growth rates by a functional system derived from these reports are used to validate HPMS traffic data. The goal is that all traffic information published by the FHWA and the States is valid and consistent.

However, it is very clear that there are still many possible sources of errors in the VMT estimation process for lower functional systems developed by transportation agencies, which result in biased VMT number production. About half of the states indicated that they had no idea how to determine the accuracy of their estimates [4]. So, developing a more accurate and efficient method in estimating VMT for lower functional classes of roadways is quite necessary and meaningful, which is the major motivation of this study.

In order to achieve this goal, the author first introduces the function of different roadway classes. Roadways are classified according to their primary functions. These classes include principal arterial roads (interstate highways, other freeways, expressways, and others), minor arterial roads, collector roads (both major and minor), and local roads [5]. Interstate highways are the highest class roads and connect major cities of the 48 U.S. contiguous states. Arterial roads, either urban or rural, include expressways without full control of access, U.S. numbered routes, and principal state routes. Collector roads serve as links between arterial roads and local roads. Local roads provide access to properties and have characteristics such as low capacity and low speed. Arterial roads focus on mobility while local roads focus mostly on land access. Collector roads strike a balance between the two. An access-mobility diagram is shown in Figure 1.1.

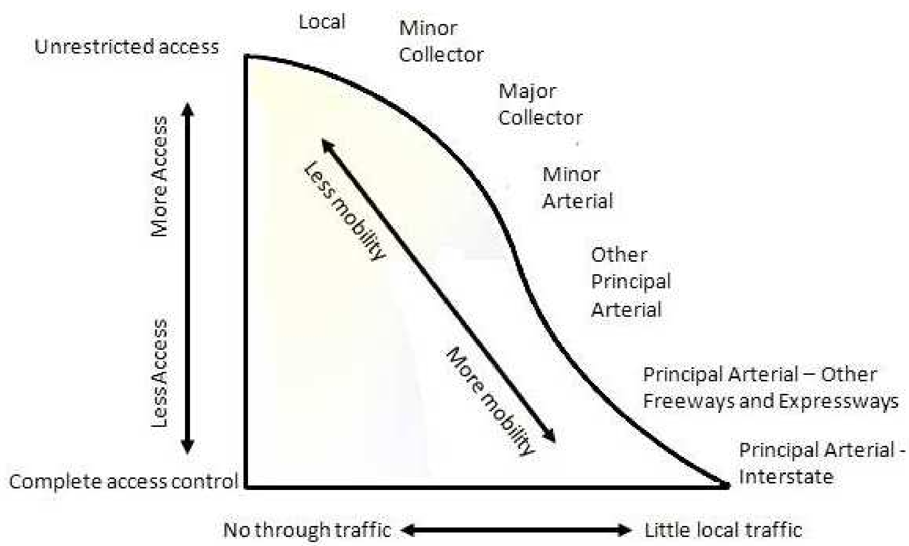


Figure 1.1: Diagram of land access mobility for each functional system (*Source*: FHWA Functional Classification Guidance, 2012 [6])

Interstates, freeways, and major arterial roads are completely monitored by HPMS. HPMS is a national level highway information system that includes data on the extent, condition, performance, use and operating characteristics of the nation's highways. Major collector roads are also covered by various traffic monitoring programs developed by state DOTs. However, traffic data collected on lower classes of roadways are limited, especially on local roads.

State DOTs and local transportation agencies traditionally use traffic volume count programs to get the VMT data they need simply by multiplying traffic count by road segment mileage. However, the focus of these traffic count programs is on higher classes of roads, primarily on arterial roads. Traffic volumes on local roads are much less frequently counted due to the difficulties in collecting such data. HPMS does not require any specific method for the sampling of local road traffic volumes.

The method to be used for estimating local road VMT is selected by respective state DOTs. For local roads, a variety of methods are employed. The most commonly used methods include a multi-year cycle traffic sample, the application of traffic growth rates as determined by automatic traffic recorders, or the application of average traffic growth at a statewide level or on minor arterial and major collector systems compared to the previous year's estimate. However, currently no consistent method has been identified and adopted by all states.

Moreover, most state DOTs are slow to develop comprehensive programs for traffic data collection on local roads, because their role is not as important as the major arterial roads–the interstates and freeways that make up the state highway system. The main reason is that the traffic is very light (10% to 30% of the total VMT is on local roads) and sporadic on local roads, and the total length of local roads can be so expansive that it makes it very expensive and difficult to collect traffic data on them.

So, even though local roads constitute a large portion (60% to 70%) [7] of the total mileage of a state's road network, much less effort has been made to estimate VMT on local roads than for higher classes of roads. Thus, the primary reason for the difficulty of estimating VMT on local roads is the lack of sufficient available traffic data on them. Recently, however, more attention has been given to local road VMT. Local road VMT has been recognized as an important component of air quality emissions from vehicles, and it is also very important for traffic accident rate analysis [8].

Local road traffic count is difficult to obtain practically, which raises the question:

Is it really necessary? Can one estimate the local road VMT through an analysis of collector road VMT and roadway network structure? In this thesis, the author tries to establish relationships between VMTs on different functional classes of roadways as a function of easily measurable network characteristics.

2. LITERATURE REVIEW

There are three different categories of VMT estimation methods: traffic-count based methods, non-traffic-count based methods, and local road specific methods.

2.1 Traffic-count Based VMT Estimation Methods

The HPMS method provides a basic traffic-count based method and is the most accepted method for estimating VMT in United States. However, since HPMS is designed to concentrate on federal-aid roads only, this method is mainly used for arterial and major collector roads for VMT estimation. The basic principle behind this kind of method is that it first obtains an adjusted 24-hr traffic count on a sample section and multiplies it by the centerline mileage of the sample section to estimate the VMT for this section. Then, the value is annualized by multiplying by the number of days in a year. Assuming that the actual mileage of roads is known, the accuracy of traffic-count based VMT estimates is determined by the accuracy of traffic data used for estimates [9]. So, if the sampling procedure is more efficient, the estimates derived will be more accurate because most of the traffic data are obtained from sampled roads in a network.

Fricker and Kumapley [9] reviewed a VMT estimation method for arterial roads and major collector roads, which was proposed by INDOT (Indiana Department of Transportation). Like the HPMS estimation method, the INDOT procedure is also count-based and follows the HPMS Field Manual [3]. The difference is that INDOT uses its own inventory database (620,000 records for Indiana), so that the INDOT estimates are more accurate than HPMS results (4,000 records for Indiana). This kind of method is preferred since it is based on actual traffic data and statistical principles. However, it still has two major shortcomings: the unavailability of local road traffic data and its original designation for high functional classes of roads.

Also, the HPMS can serve as a reliable data source for other VMT estimating methods. Rentziou *et al.* [10] developed simultaneous equation models for predicting VMT on different road functional classes and examined how different technological solutions and changes in fuel prices can affect passenger VMT. Plus, a random coefficient panel data model was developed by the author to estimate the influence of various factors (such as demographics, socioeconomic variables, fuel tax, and capacity) on the total amount of passenger VMT. The author used the natural logarithmic pattern of VMT (log-VMT) as the dependent variable and other factors as independent variables. The influence of each significant factor on VMT is assessed by the elasticity of each factor in the proposed models. Larger elasticity indicates that a certain factor is more influential on VMT. Using this method, the future VMT can be forecasted if predicted changes of influencing factors are given. This method can also assist policy markers in reducing future energy consumption and greenhouse gas emissions. Although, the author did not consider VMT on local roads in rural or urban areas in this study, the elasticities of various factors for VMT on local roads can still be obtained in the same way once the data is available. Such data can help us assess which factors are more significant for local VMT estimation.

Additionally, HPMS data also allows researchers to integrate with other data sources. The report "TxLED VMT Estimation Project" developed by Cambridge Systematics Inc. [11] evaluated potential effectiveness of the Texas Low Emission Diesel Fuel (TxLED) program based on truck VMT estimation. The truck VMT consists of three parts: pass-through truck VMT, I-X/X-I truck VMT, and internal truck VMT. I-X/X-I VMT denotes internal-to-external trips plus external-to-internal trips and refers to truck trips with one trip ending inside a major metropolitan area and one trip ending outside a major metropolitan area. The estimation method uses four data sources, including the TxDOT Statewide Analysis Model (SAM), TxDOT Highway Performance Monitoring System (HPMS) vehicle classification data, Reebie TRANSEARCH freight flow data for the State of Texas, and metropolitan-level travel models of Houston and Dallas. Based on the characteristics of different data sources, the final estimate of VMT was developed by proportioning the trip type VMT estimates from the SAM to the VMT totals developed through HPMS data. Thus, the truck VMT estimates were obtained by multiplying the distance of a given original-destination (OD) pair by the number of trucks.

Frawley [12] proposed a random selection process to collect traffic counts on local streets in order to estimate VMT for TxDOT. Compared with the historical count process used by TxDOT, the randomly selected sites were located on all types of local streets, including cul-de-sacs, and better represent the variety of local streets on the roadway networks. The author proved this procedure by conducting a statistical analysis of traffic counts performed in various urban areas. The results showed that the entire local street network was better represented through randomly selected count locations than the historical station locations TxDOT had traditionally used. Furthermore, in order to obtain a truly random sample of data each time, the author suggested that new traffic count stations should be randomly selected each time the counts were performed. This will ensure that streets not previously counted have an opportunity to be included in the randomly selected sites.

Although the traffic-count based methods are mainly used to estimate VMT for higher functional classes of roadways, about 18 states [4] still use a limited sample of short-term traffic counts or a combination of sample counts and estimated average daily traffic to estimate local and minor collector road VMT.

2.2 Non-traffic-count Based Methods

Non-traffic-count-based VMT estimation methods use non-traffic data, such as socioeconomic data (fuel sales, trip-making behavior, household size, household income, population, number of licensed drivers, and employment) to estimate VMT. Normally, traffic related data is not required. Moreover, most of these data are difficult and expensive to collect regularly, so rough updates of previously collected data are often used for estimating VMT [9], which make the estimation results obtained from this method questionable.

Stone *et al.* [13] tried to construct and test the relationships between land use, demographics, and VMT. Once such relationships are established, the future VMT can be estimated according to land use change. The data sources used in the report include residential VMT data developed from the Nationwide Personal Transportation Survey (NPTS), commercial VMT data derived from the Freight Analysis Framework (FAF), and demographic data obtained from 1990 and 2000 censuses. This method obtains VMT rates for each cluster of census tract data based on demographical characteristics. It can obtain high-resolution graphics showing the VMT distribution throughout the study region. It can also estimate current and future VMT rates associated with land use conditions and demographics.

Fricker and Kumapley [9] developed a method using a short-term cross-classification VMT forecasting model for Indiana DOT. This short-term VMT model developed for INDOT predicts the total vehicle miles driven by all licensed drivers for all vehicle types, using demographic predictions based on the population of licensed drivers, age, and gender. The main shortcoming for this method is inaccurate information reported by respondents.

Oak Ridge National Laboratory (ORNL) also proposed a method [14] called

BESTMILE to estimate VMT driven by an NHTS (National Household Travel Survey) household vehicle based on using single odometer readings to compute estimated annual mileage. The researchers from ORNL first performed an initial analysis of 2009 NHTS vehicle data. Three regressions (one for new vehicles, one for used, and one for all vehicles) were run separately to determine the relationship between vehicle age and annual miles driven. Once the regression equations were obtained, the VMT for each year was determined.

2.3 Local Road Specific VMT Estimation Methods

Local road specific VMT estimation has mainly relied on mathematical models, as well as some other tools including GIS tools and concepts from electronic engineering. Most local road specific VMT estimation methods focus on specific study areas and under certain assumptions, so these methods are hard to transfer to different situations. Moreover, the VMT estimates obtained from these methods need further validation when traffic data on local roads become available.

Zhong and Hanson [15] tried to use travel demand models (TDM) to estimate traffic volumes on low-class roads. This method does not rely on a traditional sensor-based traffic monitoring system. Two areas in the Province of New Brunswick were selected in this study, York County and the Beresford area. Major steps included building networks and traffic analysis zones (TAZs) using the TransCAD built-in four-step model to generate traffic data. After calibration and validation, this method proved to be useful and cost-effective to estimate traffic volumes on low-class roads. Moreover, this method can address the volume variations within individual groups. However, there are still some issues with this method. One issue is that the TDM approach does not assign traffic to some roads and tends to overestimate traffic on the rest. To deal with this issue, Zhong and Hanson [15] developed regression equations to calibrate the estimates based on traffic count data and the errors were reduced.

Seaver *et al.* [16] also proposed a mathematical model based on statistical analysis. Different from traditional methods, they tried to find the relationship between VMT and socioeconomic and geographical variables at the county level. In order to develop the model, 80 counties were selected at random from the state's 159 counties. The unselected counties were used for model validation. Seaver *et al.* tested 45 general variables and used several statistical strategies to derive the optimal regression models for estimating average daily traffic (ADT) on rural local roads. The results show that the models developed in this study are statistically reliable using certain stratification variables. However, there were still some shortcomings for this method. For example, the traffic volume data and census data do not update frequently, which leads to a lag between years.

Zhao and Chung [17] proposed a method using the Geographic Information System (GIS). A multiple linear regression model of average annual daily traffic (AADT) on local roadways was presented in this study. The study area was all of Broward County in South Florida. AADT data were obtained from average quarterly traffic counts in 1998 from the Broward County Metropolitan Planning Organization. The counts were adjusted by seasonal factors based on traffic data obtained from a number of permanent count stations on state roads. Four groups of predictors were examined for potential inclusion in the models: roadway characteristics, socioeconomic characteristics, expressway accessibility, and accessibility to regional employment centers. All these variables can be obtained and tested using GIS technology. Zhao and Chung [17] found that functional classification and number of lanes are the most significant variables. As long as such information is available, the AADT on local roads can be obtained with a relatively high accuracy. However, possible sources of errors need to be examined carefully in the future.

Blume *et al.*[18] implemented a methodology to estimate local road VMT in Florida based on census data and sample counts. The major difference is that they only used the GIS tool to build a local roads GIS database at the statewide level. This method made use of available census data and an intuitive correlation between travel and population density, job density, and roadway density. The density factors were used to group similar zip code tabulation areas (ZCTAs) into subregions to allow random samples taken in one subregion to represent similar ZCTAs statewide on the basis of any or all the following: population, employment rate, and roadway density. A minimum number of random samples was selected to retain statistical validity while minimizing costs to conduct traffic counts. The study identified the required number of sample counts to reach certain accuracy levels, ranging from 158 for 70-15 (15% error at the 70th percentile), to 881 for 95-10. However, this method requires a high initial level of effort to develop the local road database. Also, more work needs to be done in the future, including selection of better stratification variables to develop a more reliable and accurate GIS roadway database.

Moreover, Wang *et al.* [19] introduced a new method that incorporated concepts from electronics engineering, which develop a circuit network model and simulation to estimate AADT on local roads. First, they found a significant linear relationship between household number and the total entrance AADT of each community. Then a circuit network was modeled among which resistors, current flow, and voltage were represented by road length, AADT, and VMT, respectively. Simply put, each entrance served as a current source, and each branch had a sink current source at its mid-point. Then the circuit network model was developed, which made it possible to derive the AADT and VMT on community local roads. The most significant feature of this method is that it can estimate VMT without field data collection, which can reduce the labor load and cost dramatically. However, the shortcomings are also very conspicuous. For example, the linear relationship between the AADT and the number of households is not very convincing and needs further validation.

Qian [20] also proposed a new local road VMT estimation method in his master's degree thesis. The main idea behind his method is that one can approximately estimate ADTs on 20% of links which have higher traffic on them in a local community given the total trips generated from that local community and local road network topological measures. The ADTs on the remaining 80% of local roads can also be obtained from a linear regression model given the total number of roads in the local network.

The method proposed in this thesis is different from previous research in several aspects. First, previous research rarely considers the internal relationship between VMT and roadway density. Second, this method takes advantage of the more accurate VMT data (HPMS data on principal and minor arterial roads) to estimate VMT on lower classes of roadways. Also, the roadway densities are much easier to obtain than field traffic count data. State or city DOTs have easy access to roadway geographic information.

2.4 State Practices to Estimate Local VMT

In this section, several noteworthy state-level practices used to estimate local VMT are introduced and compared based on a survey report conducted by FHWA [4]. Since this survey was conducted by FHWA several years ago, many states might have already revised their estimating procedures. However, this report is still representative of state practices.

2.4.1 Georgia

Georgia's estimated VMT is computed based on a stratified random sample for (1) the Atlanta area, (2) non-Atlanta urbanized areas, (3) small urban areas, (4) rural local, and (5) rural minor collectors. The average AADT within each stratum times the applicable mileage yields the amount of VMT. Over 4,000 annual traffic counts area are taken for this program statewide.

2.4.2 Kansas

In Kansas, traffic count data is collected on a six-year cycle on rural minor collector roads. About 500 24-hour counts are taken each year, and the data are adjusted for season and axle and then matched to road section to estimate daily VMT by section. Growth factors and ADT are generated by county and applied to the uncounted sections.

Ten percent sample traffic count plans were applied to the rural and small communities by population groups on a nine-year cycle. ADT value by strata is formed and applied to all sections within the strata to compute daily VMT. ADT is updated every three years.

There is a 10 percent sample of local streets in 40 urban areas that are counted on a 9-year cycle. About 400 counts are taken annually. The counts are averaged and then multiplied by the local mileage reported.

2.4.3 Kentucky

The Kentucky DOT takes coverage counts by county on a three-year cycle, and VMT is based on link ADT times rural minor arterial road mileage.

The relationship of average local ADT to average rural major collector (RMC) ADT by selected county (and average urban local to urban collector roads) was determined from normal coverage counts for the collectors and a one-time count on a random sample of local road sites. One curve of local sample ADT plotted versus collector ADT was drawn based on the 28 counties selected out of 120 counties [21]. The averages for the non-sample county areas would be developed based on the relationship established and the average collector ADT for rural, small urban, and urbanized areas. Local VMT by county and area type is the average ADT times the applicable mileage.

2.4.4 Texas

The Texas DOT uses the same process for all area types. Roads are divided into groups within each county by city and pavement type, and total mileage for each type are developed. ADT is established for each stratum. The strata ADT are multiplied by the total mileage for each corresponding county (stratified by city and pavement type). For example, the urban local VMT of Brazos County, TX is calculated by multiplying total urban local ADT of all the cities (College Station, Bryan, etc.) by total urban local road mileage. All of the resulting products are then summed and averaged to yield a statewide total. In the past the default value of the ADT became the default value of the strata for the entire state. Currently the Texas DOT is transitioning to a process that randomly selects traffic counts in each county. Through this process, the median ADT values for each stratum within a county become the default values by strata within that county.

3. ANALYTICAL ESTIMATION MODELS

The main idea is to use the more accurate VMT data on higher functional classes of roads, (e.g., principal and minor arterial roads) to estimate VMT on lower functional classes of roadways, e.g., collector and local roads. In particular, if VMT on collector roads are reliable, can people use it to estimate local road VMT by taking road spacing characteristics into consideration?

The author believes there is a clear relationship between local and collector roads based on vehicle miles traveled. This can be derived by analyzing an example as illustrated in Figure 3.1, which shows the layout of a squared local community surrounded by collector roads (circumference of the square). Local roads are distributed in a grid format within this square.

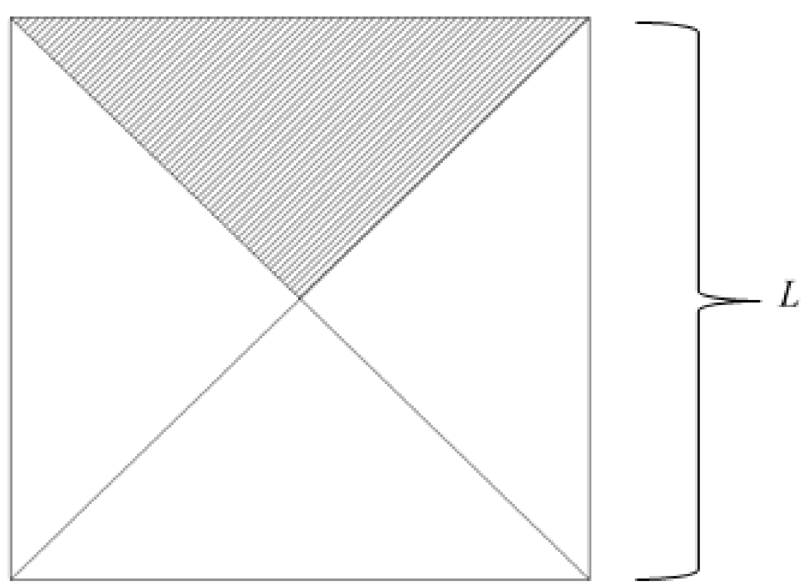


Figure 3.1: Layout of a Local Community

3.1 Average Local Distance Traveled

By using the integration method, the average local distance traveled by each traveler in the shaded area can be derived. The average distance in the rest of the area is the same as the shaded area because the residents are assumed to be equally distributed among the community.

Then, the average local distance traveled per traveler t_{local} is calculated using the total distance divided by the shaded area as follows:

$$t_{local} = \frac{2\int_0^{\frac{L}{2}} x(\frac{L}{2} - x)dx}{\frac{1}{2} \times \frac{L}{2} \times L} = \frac{L}{6}. \tag{3.1}$$

The author further considers a more realistic situation in which the traveler travels on grid local roads, that is, the traveler does not go along a Euclidean distance, but follows a grid distance.

Figure 3.2 shows the small cell which is within the shaded area in Figure 3.1.

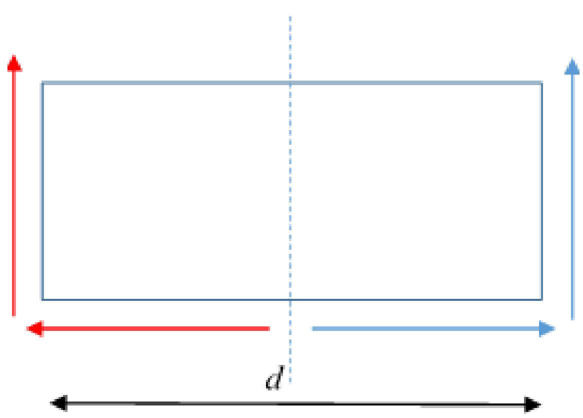


Figure 3.2: Layout of the Small Cell

Assume the local roads are distance d apart from each other. A traveler has a choice to go either through the left or right street up to the collector road. Travelers in the left half are assumed to go through the left street up and those in the right half go through the right street up, regardless of whether their destination is west or east. This assumes that the collector roads are much faster than the local roads so that travelers attempt to get to the collector roads as soon as possible. The violations of this assumption are reflected by calibrated coefficients in the final models. In this case, the average local distance is $\frac{L}{6} + \frac{d}{4}$.

3.2 Average Collector Road Distance Traveled

Using the same procedure, the average collector road distance traveled per traveler is $\frac{D}{6} + \frac{L}{4}$. Here D represents the spacing of minor arterial roads.

3.3 Average Minor Arterial Road Distance Traveled

First, the spacing of principal arterial roads is defined as S. Principal arterial is the highest roadway classification. It consists of interstate, other freeways and expressways, and other principal arterial roads according to Highway Functional Classification Concepts, Criteria and Procedures [5] developed by US FHWA. Minor and principal arterial roads are assumed to be in a grid network. Moreover, the author also assumes that principal arterial roads are much faster than minor arterial roads, so that travelers will still get to the principal arterial roads as soon as possible if they need to travel a long way. Therefore, the average minor arterial road distance is still derived using the previous procedure, which is $\frac{S}{6} + \frac{D}{4}$.

3.4 Average Principal Arterial Road Distance Traveled

For principal arterial roads, VMT data can be obtained from HPMS. HPMS is a nationwide inventory system of all public road mileage. HPMS estimates are based on actual data of vehicle movement on a road segment and the centerline miles of the segment, which provide us with high accuracy VMT data. So, HPMS VMT estimation data on principal arterial roads can be used in practice.

3.5 VMT Ratio Analysis

In this section, the author explores the major factors that determine the ratio of VMT on different functional classes of roadways.

3.5.1 Squared Local Community

The ratio between average local road distance and average collector road distance is:

$$ratio = \frac{L/6 + d/4}{D/6 + L/4}. \tag{3.2}$$

Then, it is necessary to find the road density in relation to the parameters S and D. Take a collector road as an example. A grid network of collector roads has a number n of horizontal and vertical lines, respectively, and each small square has a side size of L. The total collector road mileage is $2n^2L$ while the total area for this road mileage is n^2L^2. Therefore, the collector road density, denoted by ρ_2 can be expressed as $\rho_2 = 2/L$.

Similarly, the principal arterial road, minor arterial road and local road densities can be expressed as $\rho_4 = 2/S$, $\rho_3 = 2/D$, and $\rho_1 = 2/d$. In the subsequent derivations, the author also assumes that $S \gg D, D \gg L, andL \gg d$, where $\gg$ means sufficiently large compared with the second term. This assumption is based on an extreme situation, which is used to simplify the following derivation procedure and get clean terms. Similarly, the volitions of this assumption are reflected by calibrated coefficients in derived models.

Additionally, the author ignores the within community trips and assumes each trip leaves the collector roads by getting onto a minor principal road. Therefore, the ratio of distances on collector and local roads of a trip (average trip) is equal to the ratio of local road VMT and collector road VMT.

So, the ratio between local road VMT and collector road VMT can be expressed as follows.

$$\begin{aligned}\frac{VMT_L}{VMT_C} &= \frac{L/6+d/4}{D/6+L/4}\\ &\approx \frac{L/6+d/4}{D/6}\\ &\approx \frac{\rho_3}{\rho_2}+\frac{3}{2}\cdot\frac{\rho_3}{\rho_1}.\end{aligned} \tag{3.3}$$

When $\rho_2 \to \infty$, the density of collector roads is much larger than the density of minor arterial roads. So the first term is equal to 0 and the ratio$=\frac{3}{2}\cdot\frac{\rho_3}{\rho_1}$; when $\rho_2 \to 0$, it indicates that the spacing of collector roads is very large and almost equal to the spacing of minor arterial roads. So $\rho_2 = \rho_3$, and the ratio$=1+\frac{3}{2}\cdot\frac{\rho_3}{\rho_1}$. Therefore, the reasonable ratio range is $(\frac{3}{2}\cdot\frac{\rho_3}{\rho_1}, 1+\frac{3}{2}\cdot\frac{\rho_3}{\rho_1})$.

Based on the assumption that $D \gg L \gg d$, $\frac{\rho_3}{\rho_1}$ is much smaller than $\frac{\rho_3}{\rho_2}$, the author takes the logarithmic value of Equation 3.3, which leads to $ln(VMT_L) = ln(VMT_C) + ln\rho_3 - ln\rho_2$. In a general sense, for the purpose of establishing a regression equation and allowing noise effects due to uneven distribution of roadways and trips, a regression equation is proposed as follows:

$$ln(VMT_L) = \alpha_1 ln(VMT_C) + \alpha_2 ln\rho_3 + \alpha_3 ln\rho_2 + \alpha_0 \tag{3.4}$$

with the coefficients $\alpha_0, \alpha_1, \alpha_2, \alpha_3$ are calibrated using field data.

Similar to Equation 3.3, the ratio between the collector road VMT and the minor arterial road VMT is calculated as follows.

$$\begin{aligned}
\frac{VMT_C}{VMT_{MA}} &= \frac{D/6 + L/4}{S/6 + D/4} \\
&\approx \frac{D/6 + L/4}{S/6} \\
&\approx \frac{\rho_4}{\rho_3} + \frac{3}{2} \cdot \frac{\rho_4}{\rho_2}. \qquad (3.5)
\end{aligned}$$

It is also possible to develop a regression equation as

$$ln(VMT_C) = \alpha_1 ln(VMT_{MA}) + \alpha_2 ln\rho_4 + \alpha_3 ln\rho_3 + \alpha_0. \qquad (3.6)$$

To develop a relationship between local road VMT and minor arterial road VMT, the following calculation will work:

$$\begin{aligned}
\frac{VMT_L}{VMT_{MA}} &= \frac{VMT_L}{VMT_C} \times \frac{VMT_C}{VMT_{MA}} \\
&\approx (\frac{\rho_3}{\rho_2} + \frac{3}{2} \cdot \frac{\rho_3}{\rho_1}) \times (\frac{\rho_4}{\rho_3} + \frac{3}{2} \cdot \frac{\rho_4}{\rho_2}) \\
&= \frac{\rho_4}{\rho_2} + \frac{3}{2} \cdot \frac{\rho_4}{\rho_1} + \frac{3}{2} \cdot \frac{\rho_4 \rho_3}{{\rho_2}^2} + \frac{9}{4} \cdot \frac{\rho_4 \rho_3}{\rho_1 \rho_2} \\
&\approx \frac{\rho_4}{\rho_2} + \frac{3}{2} \cdot \frac{\rho_4}{\rho_1}.
\end{aligned} \qquad (3.7)$$

Similarly, two formats of a liner regression model can be used to represent the correlation between local road VMT and minor arterial road VMT as follows:

$$\begin{aligned}
\frac{VMT_L}{VMT_{MA}} &= \alpha_1 \frac{\rho_4}{\rho_2} + \alpha_2 \frac{\rho_4}{\rho_1} + \alpha_0 \qquad (3.8) \\
ln(VMT_L) &= \alpha_1 ln(VMT_{MA}) + \alpha_2 ln\rho_4 + \alpha_3 ln\rho_3 + \alpha_4 ln\rho_2 + \alpha_5 ln\rho_1 + \alpha_0. (3.9)
\end{aligned}$$

Figure 3.3 illustrates layout of a large network with road spacings used for the above derivation, and it also gives an example of a trip going from the local community to its destination (arrow paths in red and yellow).

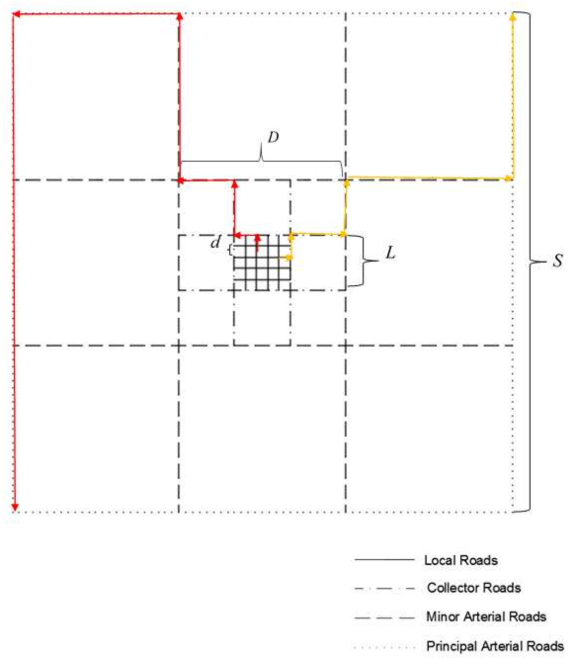


Figure 3.3: Structural Layout of Roadways Used in Derivation (the lengths of d, L, D and S do not reflect the assumed lengths in derivation)

3.5.2 Rectangular Local Community

The author further assumes that the local community layout to have rectangular shape as shown in Figure 3.4.

The community is surrounded by collector roads with a length of L and width of W ($L \geq W$). The author further supposes that $W = \beta L$ and $\beta \in (0, 1]$. In a special case where $\beta = 1$, the length and width of the rectangle are equal, and the community becomes a squared shape, which is the most common shape and the

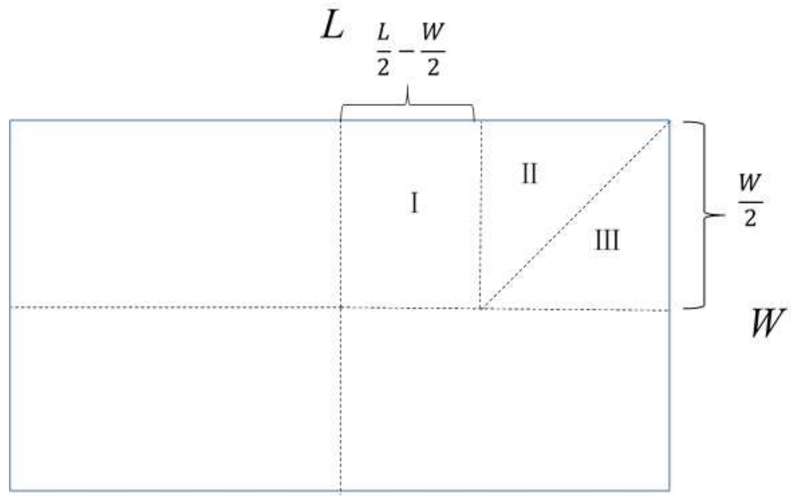


Figure 3.4: A Rectangular Local Community Surrounded by Collector Roads

standard set at the beginning of this chapter's study.

As shown in the earlier the squared community, the author still assumes that the rectangular shaped layout will allow travelers to get to the collector roads as soon as possible, and that travel demand is uniformly distributed within the area. The author divides the area into four sections as in Figure 3.4, all of which are equivalent in terms of VMT ratio between local and collector roads. Therefore, only the upper right quarter of the rectangle is examined for calculating average local distance traveled by each traveler, and that is divided into three sections:

- Section I

A rectangle the size of $(\frac{L}{2} - \frac{W}{2}) \times \frac{W}{2}$, in which travelers use local roads to get to the collector road.

- Section II

A right triangle of $\frac{W}{2} \times \frac{W}{2}$, in which travelers go up to the collector road first.

- Section III

A right triangle of $\frac{W}{2} \times \frac{W}{2}$ in which travelers arrive at the collector road on the right first.

In section I, the average local distance traveled is $\frac{W}{4}$.

In sections II and III, the average local distance traveled is calculated as follows:

$$t'_{local} = \frac{\int_0^{\frac{W}{2}} \frac{x}{2} \cdot x \cdot dx}{\frac{1}{2} \times \frac{W}{2} \times \frac{W}{2}} = \frac{W}{6}. \tag{3.10}$$

Therefore, the average local distance for all three sections is:

$$\begin{aligned} t_{local} &= \frac{\frac{W}{4} \times \frac{L-W}{2} \times \frac{W}{2} + \frac{W}{6} \times \frac{W^2}{4}}{\frac{LW}{4}} + \frac{1}{4}d \\ &= \frac{W}{4}(1 - \frac{W}{3L}) + \frac{1}{4}d \\ &= \frac{(3-\beta)\beta}{12}L + \frac{1}{4}d \end{aligned} \tag{3.11}$$

where d is the spacing between local roads.

When $\beta = 1$, Equation 3.11 becomes $\frac{L}{6}$, exactly the same as for the community with a square layout as derived earlier. Then the collector and minor arterial road density need to be determined. Take a collector road as an example. A grid network of collector roads has m horizontal lines with a spacing of W and m vertical lines with a spacing of L. The total collector road mileage is $m^2(L+W)$ while the total area for this road mileage is m^2LW. Therefore, the collector road density, denoted by ρ_2 can be expressed as $\rho_2 = \frac{L+W}{LW} = \dfrac{\beta+1}{\beta L}$. Similarly, the minor arterial road density can be expressed as $\rho_3 = \frac{\gamma+1}{\gamma D}$, where D is the length of the rectangle surrounded by minor arterial roads and γD is the width ($\gamma \in (0,1]$). Note that, the density of local road ρ_1 is still equal to $\frac{2}{d}$ as discussed in square-shaped community situation.

Subsequently, the average distance traveled on collector roads donated by $d_{collector}$

can be calculated as expressed in the following equation:

$$\begin{aligned} t_{collector} &= \frac{(3-\gamma)\gamma}{12}D + \frac{\frac{W}{4} \times \frac{W^2}{4} + \frac{L+W}{4} \times \frac{L-W}{2} \times \frac{W}{2}}{\frac{LW}{4}} \\ &= \frac{(3-\gamma)\gamma}{12}D + \frac{1}{4}L. \end{aligned} \tag{3.12}$$

Thus, based on the assumption that demand is uniformly distributed in the community, the ratio between local road VMT and collector road VMT can be derived as follows:

$$\begin{aligned} \frac{VMT_L}{VMT_C} &= \frac{\frac{(3-\beta)\beta}{12}L + \frac{1}{4}d}{\frac{(3-\gamma)\gamma}{12}D + \frac{1}{4}L} \\ &\approx \frac{\frac{(3-\beta)\beta}{12}L + \frac{1}{4}d}{\frac{(3-\gamma)\gamma}{12}D} \\ &\approx \frac{(3-\beta)(\beta+1)}{(3-\gamma)(\gamma+1)} \cdot \frac{\rho_3}{\rho_2} + \frac{6}{(3-\gamma)(\gamma+1)} \cdot \frac{\rho_3}{\rho_1}. \end{aligned} \tag{3.13}$$

So, the relationship between local road and collector road VMT can be expressed in a general format as follows:

$$\frac{VMT_L}{VMT_C} = \beta_1\frac{\rho_3}{\rho_2} + \beta_2\frac{\rho_3}{\rho_1} + \beta_0. \tag{3.14}$$

where β_i are the parameters. The result shows that even as the shape of the local community becomes rectangular, the major factors in the relationship derived under the square shaped situation remain unchanged, which indicates our major result is robust.

3.5.3 Circular Local Community

The author envisions the major terms, $\frac{\rho_3}{\rho_2}$ and $\frac{\rho_3}{\rho_1}$, remain as the explanatory variables regardless of network density and neighborhood shape. The network density, shape, and uneven distribution of travelers are reflected by the coefficients $\beta_0, \beta_1, \beta_2$, respectively, that are to be calibrated with data. To further prove the robustness, the author investigated the distribution and variables of a local community surrounded by a collector road which had the shape of a circle, as illustrated in Figure 3.5.

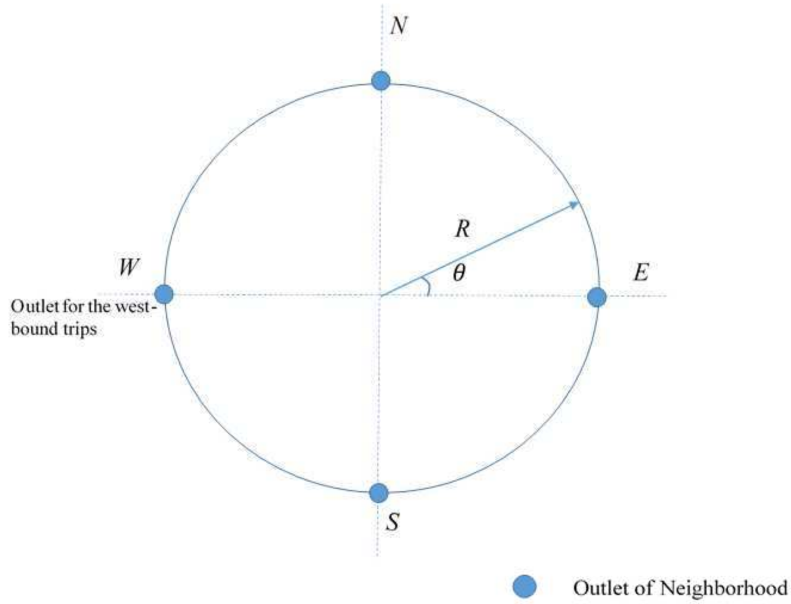


Figure 3.5: Circular Local Community Surrounded by Collector Roads

Consider a continuous case in which trip demands are generated uniformly within the circular shaped community. A trip generated at any location within the circle has an equal probability to go any one of the four directions. The trip leaves the community at one of the four 'outlets' (represented by the four smaller circles at the four corners). Each trip follows the radius line (shortest possible local road) to the nearest collector road, after which it takes the shortest outlet before continuing on the collector road until the traveler gets to the minor arterial roads. Figure 3.6 shows the process.

The total local distance traveled can be represented as follows:

$$\int_0^{2\pi}\int_0^R (R-r)crdrd\theta = \frac{c\pi R^3}{3}. \tag{3.15}$$

where c is a probability density constant for traveler presence, and $R-r$ is the shortest local distance traveled to the nearest collector road on the ring, regardless of the final direction chosen.

The total number of trips is

$$\int_0^{2\pi}\int_0^R crdrd\theta = c\pi R^2. \tag{3.16}$$

Therefore, the average local distance traveled is $\frac{c\pi R^2}{2\pi Rc} = \frac{R}{2}$.

Then, the average collector VMT per trip on the ring only is calculated as follows. The additional collector road VMT before hitting a minor arterial road depends on the density of the minor arterial road.

$$\begin{aligned}
&= \int_0^{\frac{\pi}{2}}\int_0^R \frac{(\pi-\theta)R + (\frac{\pi}{2}-\theta)R + \theta R + (\frac{\pi}{2}+\theta)R}{4} crdrd\theta \\
&= \int_0^{\frac{\pi}{2}}\int_0^R c\frac{\pi}{2}Rrdrd\theta \\
&= \frac{c\pi^2R^3}{12}.
\end{aligned} \tag{3.17}$$

The four terms in the numerator of the first line represent collector road distance to the west, north, east, and south direction, respectively. This equation is for $\theta \subset [0, \frac{\pi}{2}]$.

If the trips are uniformly generated in the circle, all four quadrants are symmetric in terms of VMT, given that the four directions have an equal share of the final destination. Therefore, the total collector road distance is $\frac{1}{3}c\pi^2R^3$. So, the average collector road distance on the ring is calculated as follows:

$$\frac{c\pi^2R^3}{3c\pi R^2} = \frac{\pi}{3}R. \tag{3.18}$$

As a result, the local and collector VMT ratio for the average trip becomes

$$\frac{VMT_L}{VMT_C} = \frac{\frac{R}{3}}{\frac{\pi R}{3}} = \frac{1}{\pi} = constant. \tag{3.19}$$

Next, in the same spirit, if a minor arterial road has a radius of D, also assuming minor arterial roads as circles, the total collector road miles can be approximated to $\frac{\pi R}{3} + \frac{D}{3}$, assuming $D \gg R$ (meaning R is very small compared with D).

Therefore, the ratio of local VMT and collector road VMT is equal to

$$\frac{VMT_L}{VMT_C} = \frac{\frac{R}{3}}{\frac{\pi R}{3} + \frac{D}{3}} \approx \frac{R}{D}. \tag{3.20}$$

In this case, the collector road density ρ_2 is calculated using half the circumference divided by the total area of the local community. The result is as follows:

$$\rho_2 = \frac{\pi R}{\pi R^2} = \frac{1}{R}. \tag{3.21}$$

The density for minor arterial roads can also be obtained as: $\rho_3 = \frac{1}{D}$.

So, the ratio of local road VMT and collector road VMT becomes

$$\frac{VMT_L}{VMT_C} = \frac{\rho_3}{\rho_2}. \tag{3.22}$$

The reason for using circular shapes to form a larger circular shape is that a larger polygon can be formed by many smaller polygons, and each smaller polygon has an inscribed circle. So, all the polygons can be substituted by circles. Even if there are some errors, the errors are not significant for their small magnitude. Figure 3.6 illustrates that a large hexagon can encompass a large number of smaller hexagons, and each circle can be used to approximate the hexagon. The circles in dashed lines are the approximations of hexagons. The red line shows the real path of a trip, which is approximated by the yellow line according to our analysis.

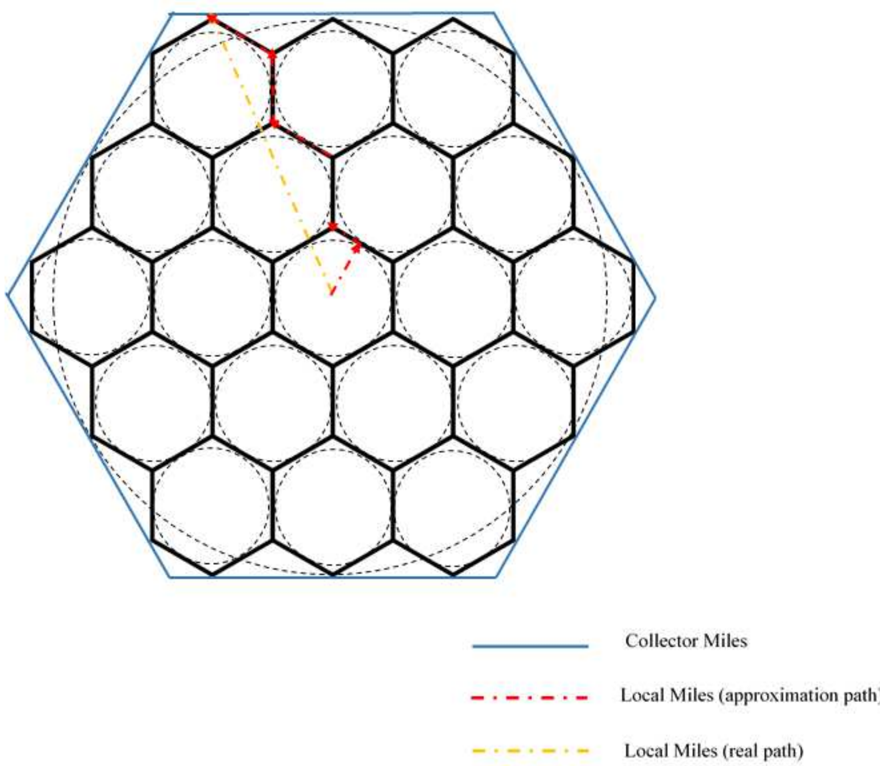


Figure 3.6: Large hexagon (circle) contains small hexagons (circles)

The results obtained confirm the accuracy of similar results from the assumptions of square-shaped (or grid network) neighborhoods.

4. VMT ESTIMATION PROCEDURE AND VALIDATION

4.1 Introduction

As a means to examine the analytical results proposed earlier, the author used 30 different types of local community networks for simulation. These configurations were first designed based on examples from Southworth and Ben-hoseph [22]. For simplicity and comparison, only networks with the same area in a square shape were chosen. The length of each side is 8 units long in TransCAD, so the total area of each community is 64. The speed for local and collector roads was set at 15 and 40, respectively. Figure 4.1 shows the layouts of the 30 simulated local networks. The four side collector roads are represented by red lines, and the local roads are shown as green lines.

TransCAD was used in the simulation to get the VMT data on each functional road. For each neighborhood, the author set 64 trip generator zones (each zone contains 3 households) that represent the traffic demand origins, and all travelers originate from the center of the trip generator zone. The traffic demand in each trip generator zone is set to be 10 units. So the total traffic demand is 640 units for a community. Although the number is not very big, such a setting is for simplifying the simulation process and will not affect the final results (VMT ratios). Four trip generator zones at the corners of each community were constructed to let travelers go along collector roads through these corners, so as to get to higher class roads and reach their destinations. The volumes that correspond to these four zones are equal, which is 160 demand units each. As mentioned above, traffic demand is assumed to be uniformly distributed in each community. Also, the traffic demand set up in simulation is for one weekday. Here the author only considers trips going outside the

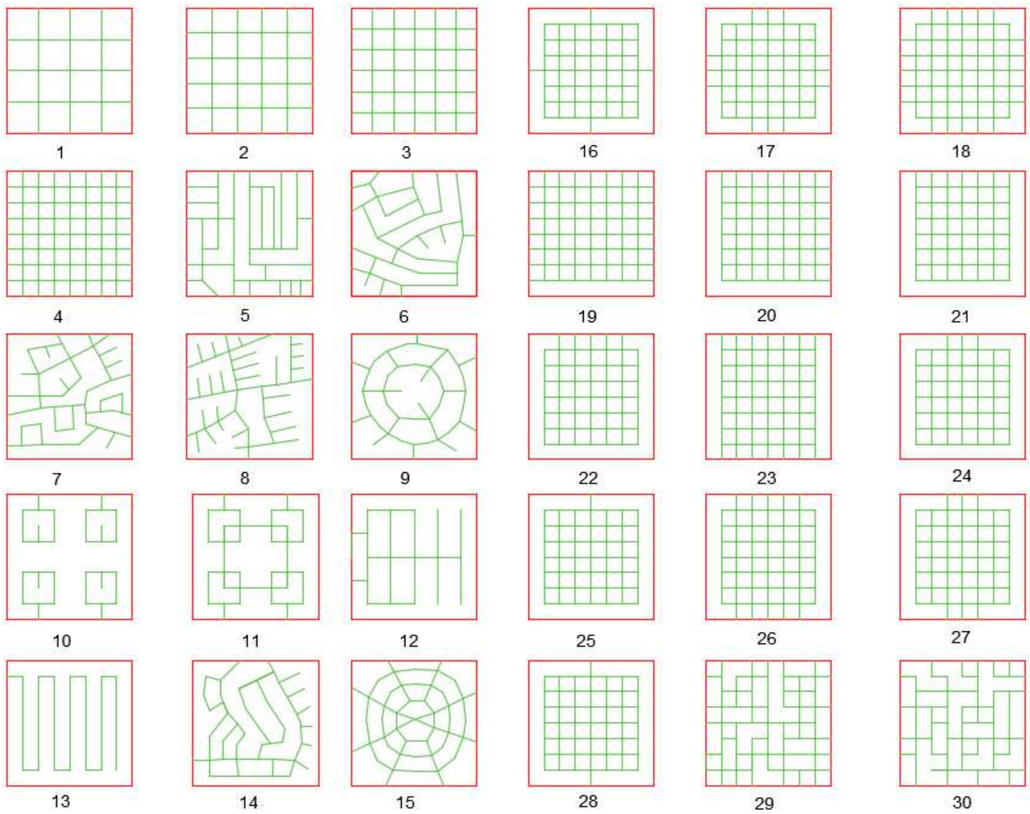


Figure 4.1: Layouts of 30 Simulation Networks (with each network's ID)

community or trips within the community. Return trips are not included.

Figure 4.2 shows the roadway network structures used in the simulation process. The speed for minor arterial roads is set to be 60 and 75 for principal arterial roads. The 30 local networks mentioned at the very beginning of this introduction (the figure only shows local network with ID=1) are analyzed under different combinations of principal-minor arterial road networks (left two networks) and minor arterial-collector road networks (middle three networks), which helps enforce the real-world comparison of the simulation process to actual network patterns.

Figure 4.3 is an example of the simulation result for the local community network

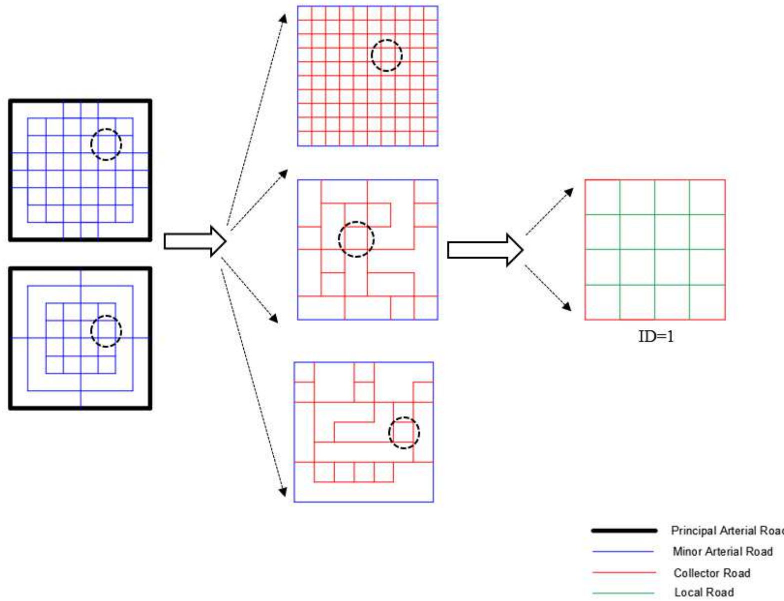


Figure 4.2: Network with Layered Classes of Roadways Functional As Envisioned in the Analysis

where ID=1. There are 64 small green squares uniformly scattered within the community, which are the trip generator zones. Four small green squares are set at the corners and represent the trip generator zones that allow travelers to get to higher class roads. The resulting volumes are shown on each link and each trip generation zone.

The simulation results of the 30 local networks are shown in Table 4.1. Column 2 is the VMT on local roads. The author first calculated the VMT on each local road segment (traffic on the road segment × length of the road segment), and then added up all local road segments' VMT to generate the total numbers. Columns 3 and 4 represent VMT on collector roads. Column 3 represents the first part of VMT on four collector side roads, and Column 4 covers the VMT for travelers going to minor arterial roads. It is the same situation for minor arterial road VMT as well column

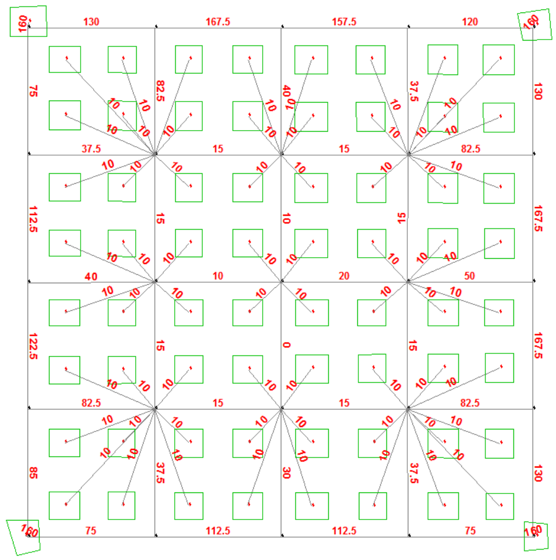


Figure 4.3: Example (ID=1) Community Output for Simulation

5 and 6. All the VMT data have the same unit, which does not affect the results of VMT ratios. Columns 7 to 10 are roadway densities of principal arterial roads, minor arterial roads, collector roads, and local roads, respectively. For the density of each roadway class, for example, the density of collector roads (ρ_2) is calculated using the total length of collector roads divided by the area surrounded by minor arterial roads. Other densities are calculated in a similar way. This adjustment ensures that the densities used are consistent with convention.

In addition, when roadway networks are not in a grid, it is impossible to just use roadway spacing. In that case, density is practically a more convenient measure for application.

In Equations 3.3 and 3.4, the author proposes two general formats for regression analysis, which are the density ratio format and logarithmic format. These formats are powerful in that they allow calibration of coefficients to allow for various network

Table 4.1: Simulation Results for the 30 Networks

ID	VMT_L	VMT_{C1}	VMT_{C2}	VMT_{MA1}	VMT_{MA2}	ρ_4	ρ_3	ρ_2	ρ_1
1	1596.90	3879.37	12175	39312	187022	0.0031	0.0188	0.2250	0.7498
2	1468.07	4032.25	12175	39312	187022	0.0031	0.0188	0.2250	0.9996
3	1252.86	4292.82	12175	39312	187022	0.0031	0.0188	0.2250	1.2497
4	1044.92	4459.63	12175	39312	187022	0.0031	0.0188	0.2250	1.7495
5	1537.15	4359.36	12175	39312	187022	0.0031	0.0188	0.2250	1.1839
6	1705.91	4246.34	12175	39312	220800	0.0031	0.0141	0.2250	0.9759
7	1875.50	4143.17	12175	39312	220800	0.0031	0.0141	0.2250	0.9916
8	2006.39	4101.55	12175	39312	220800	0.0031	0.0141	0.2250	0.9988
9	1933.45	3947.55	12175	39312	220800	0.0031	0.0141	0.2250	0.8251
10	2256.31	5118.64	12175	39312	220800	0.0031	0.0141	0.2250	0.7947
11	2295.96	4453.15	8560	22800	112213	0.0052	0.0313	0.1528	0.9366
12	4740.84	3750.20	8560	22800	112213	0.0052	0.0313	0.1528	0.7206
13	14608.41	5118.66	8560	22800	112213	0.0052	0.0313	0.1528	0.7472
14	2613.75	4265.87	8560	22800	112213	0.0052	0.0313	0.1528	0.9250
15	1596.70	3930.54	8560	22800	112213	0.0052	0.0313	0.1528	1.1433
16	1908.87	4118.84	8560	22800	132480	0.0052	0.0234	0.1528	1.3768
17	1388.79	4284.47	8560	22800	132480	0.0052	0.0234	0.1528	1.5007
18	1199.35	4394.54	8560	22800	132480	0.0052	0.0234	0.1528	1.6251
19	1313.84	4152.41	8560	22800	132480	0.0052	0.0234	0.1528	1.6408
20	1832.15	4350.06	8560	22800	132480	0.0052	0.0234	0.1528	1.5303
21	2462.78	5118.63	12160	25344	130916	0.0045	0.0268	0.1301	1.4244
22	2778.49	5118.63	12160	25344	130916	0.0045	0.0268	0.1301	1.3931
23	1559.06	3918.23	12160	25344	130916	0.0045	0.0268	0.1301	1.5330
24	3100.33	5118.63	12160	25344	130916	0.0045	0.0268	0.1301	1.3619
25	3661.29	5118.63	12160	25344	130916	0.0045	0.0268	0.1301	1.3306
26	1876.07	3918.23	12160	25344	154560	0.0045	0.0201	0.1301	1.4707
27	2196.07	3918.23	12160	25344	154560	0.0045	0.0201	0.1301	1.4082
28	2756.47	3918.23	12160	25344	154560	0.0045	0.0201	0.1301	1.3460
29	1142.77	4491.91	12160	25344	154560	0.0045	0.0201	0.1301	1.4377
30	1350.51	4283.75	12160	25344	154560	0.0045	0.0201	0.1301	1.2027

structures (e.g., noises). Next, mathematical methods are used to derive the specific regression models for these two formats.

4.2 Connectivity Measures

First, the concept of connectivity is introduced to categorize all the local networks set up. The reason for categorizing the local networks is that the author wants to find the regression equations according to neighborhood categories.

The 30 local networks set up in the simulation process can be divided into several categories based on the connectivity of a certain network. According to the Victoria Transport Policy Institute [23], connectivity refers to the directness of links and the density of connections in path or road networks. A well-connected road or path network has many short links, numerous intersections, and minimal dead-ends (cul-de-sacs) [24]. Definitions from Tresidder's paper [24], which are necessary for a greater understanding of the connectivity measures, are provided in Table 4.2 and Figure 4.4. Dill [25] evaluated various measures of network connectivity for the purpose of increasing walking and biking based on a project in Portland. In this paper, the author chose the Connected Node Ratio (CNR) as the criterion to categorize 30 local networks.

Table 4.2: Connectivity Definitions. (*Source*: Tresidder, 2004 [24])

Word/Phase	Definition
Link	A roadway or pathway segment between two nodes. A street between two intersections or from a dead end to an intersection.
Node	The endpoint of a link, either a real node or a dangle node
Real Node	The endpoint of a link that connects to other links. An intersection.
Dangle Node	The endpoint of a link that has no other connections. A dead-end or cul-de-sac

The CNR is the number of street intersections divided by the total number of

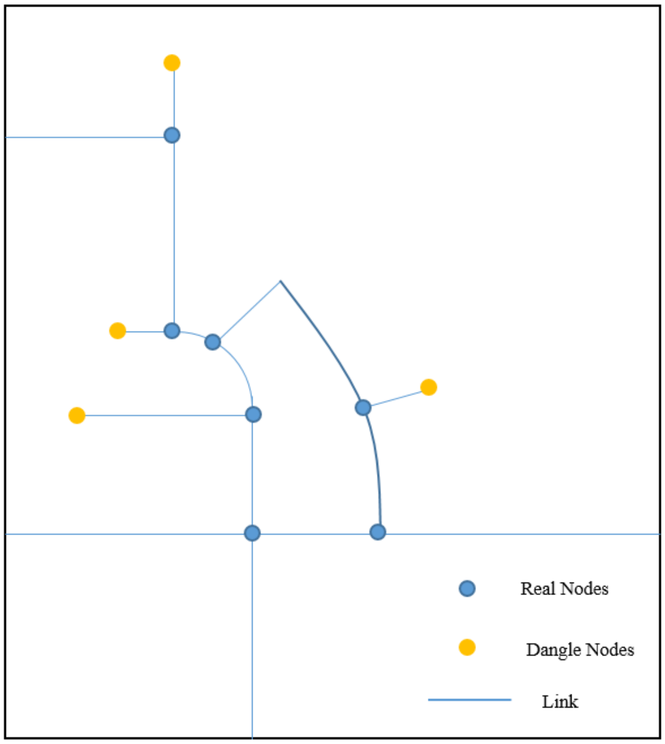


Figure 4.4: Connectivity Definitions

intersections and cul-de-sacs.

$$\text{Connected Node Ratio} = \frac{\#\ \text{Real Nodes}}{\#\ \text{Total Nodes (real+dangle)}} \tag{4.1}$$

A higher CNR indicates that there are relatively few cul-de-sacs and better accessibility between points, which leads to a higher level of connectivity. The calculated CNR of local networks are shown in Table 4.3.

The author divided the 30 local networks into three categories based on the CNR measure. The three categories are low connectivity (LC) where $CNR \in [0, 0.5]$, medium connectivity (MC) where $CNR \in (0.5, 0.9]$, and high connectivity (HC) where $CNR \in (0.9, 1.0]$. The threshold points were chosen subjectively. $CNR = 1$

Table 4.3: Measure of Connected Node Ratio for the 30 Networks

ID	Real Node	Dangle Node	Connected Node Ratio (CNR)
1	9	0	1.00
2	16	0	1.00
3	25	0	1.00
4	49	0	1.00
5	23	0	1.00
6	19	3	0.86
7	21	5	0.81
8	27	24	0.53
9	18	3	0.86
10	8	4	0.67
11	12	0	1.00
12	9	4	0.69
13	0	1	0.00
14	20	6	0.77
15	25	0	1.00
16	45	0	1.00
17	45	0	1.00
18	45	0	1.00
19	49	0	1.00
20	48	0	1.00
21	47	0	1.00
22	45	0	1.00
23	49	0	1.00
24	45	0	1.00
25	45	0	1.00
26	45	0	1.00
27	45	0	1.00
28	45	0	1.00
29	43	0	1.00
30	32	1	0.97

means that there is no cul-de-sac in a network (like a grid-network). Since there is only one network (ID=13), it falls the first category where $CNR \leq 0.5$ and five additional networks, with CNR in the same category, are set up for regression analysis using Equations 3.3, 3.4, 3.5, and 3.6 . Figure 4.5 shows the layouts of the five additional local networks as well as the initial Network No.13.

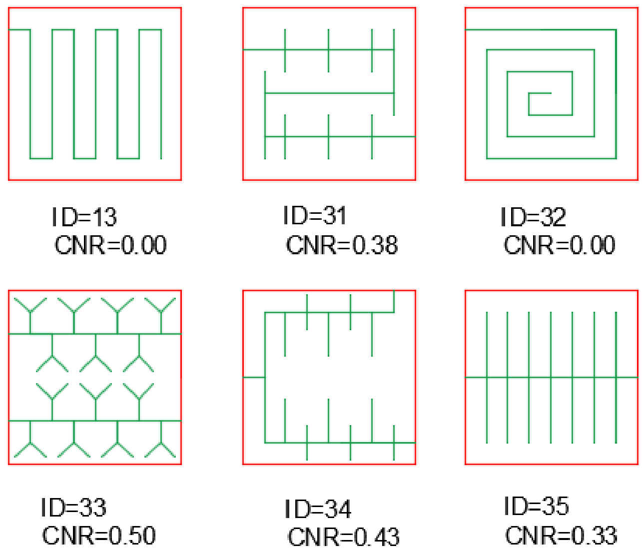


Figure 4.5: Layout of Six Networks ($0 \leq CNR \leq 0.5$)

The summary of the classification is given in Table 4.4. In the next section, regression models are calibrated under each of the three categories.

4.3 Density Ratio Model

4.3.1 Local Road VMT vs. Collector Road VMT

In a previous analysis, the author proposed the following regression model for the relationship between the VMT ratio and road densities,

$$\frac{VMT_L}{VMT_C} = \alpha_1 \frac{\rho_3}{\rho_2} + \alpha_2 \frac{\rho_3}{\rho_1} + \alpha_0, \tag{4.2}$$

where α_1 and α_2 are coefficients and α_0 is noise error coefficient. The coefficients are calibrated using the simulation data obtained in the last step. The specific regression

Table 4.4: Network Classifications: CNR

Low		Medium		High	
ID	CNR	ID	CNR	ID	CNR
13	0.00	6	0.86	1	1.00
31	0.38	7	0.81	2	1.00
32	0.00	8	0.53	3	1.00
33	0.50	9	0.86	4	1.00
34	0.43	10	0.67	5	1.00
35	0.33	12	0.69	11	1.00
		14	0.77	15	1.00
				16	1.00
				17	1.00
				18	1.00
				19	1.00
				20	1.00
				21	1.00
				22	1.00
				23	1.00
				24	1.00
				25	1.00
				26	1.00
				27	1.00
				28	1.00
				29	1.00
				30	0.97

models are obtained using the network data within each category from low to high connectivity, as described below.

4.3.1.1 Neighborhoods of Low Connectivity

The final format of the regression model of networks with low connectivity based on the six local networks (ID=13, 31, 32, 33, 34, 35) is as follows.

$$\frac{VMT_L}{VMT_C} = -9.52\frac{\rho_3}{\rho_2} + 63.47\frac{\rho_3}{\rho_1} - 0.12. \tag{4.3}$$

The R^2 value is only 0.18, which shows that this regression equation is very weak in representing the correlation between the VMT ratio and densities of networks with low connectivity. The reason is very clear that networks with small CNR have many cul-de-sacs and very few intersections, which result in a lack of short links for travelers to choose from. So, the VMT on local roads in these networks does not follow the theoretical derivation the author first proposed.

Actually, VMT changes dramatically based on the specific pattern according to Figure 4.6. If there is only one exit to the collector roads, the local VMT will be very large since there is only one link allowing travelers to access collector roads. However, when there are two or more exits, the VMT drops to a much smaller value, which indicates too much deviation from the assumptions for the analytical derivation.

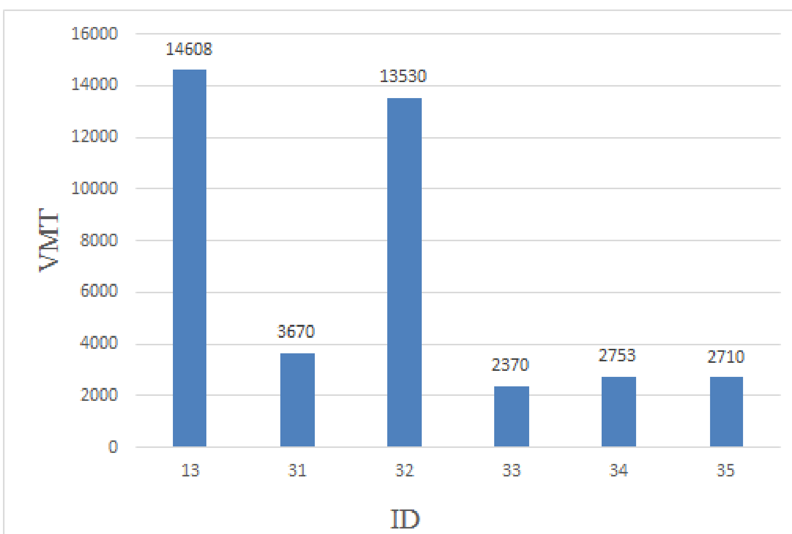


Figure 4.6: Local VMT of Low Connectivity Networks

For the case of low CNR, the average errors using Equation 4.4 are summarized in Table 4.5.

$$\text{Error}(\%) = \frac{|\text{Model Result} - \text{Ratio}|}{\text{Ratio}} \times 100\% \tag{4.4}$$

Table 4.5: Local VMT Estimates for Low CNR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
13	1.0679	0.5827	45.44%
31	0.2124	0.4457	109.85%
32	0.7823	0.4467	42.90%
33	0.1869	0.1167	37.54%
34	0.1685	0.5692	237.73%
35	0.1663	0.4234	154.57%
		Average Error=	104.67%

Table 4.5 shows an average relative error of 104.67%, which is too large to accept. So the roadway density model is not applicable for local networks with very low connectivity ($0 \leq CNR \leq 0.5$).

4.3.1.2 Neighborhoods of Medium Connectivity

The regression model calibrated by local networks with medium connectivity ($0.5 < CNR \leq 0.9$) using the seven example networks (ID=6, 7, 8, 9, 10, 12, 14) as shown in Table 4.4 is as follows.

$$\frac{VMT_L}{VMT_C} = -1.31\frac{\rho_3}{\rho_2} + 15.69\frac{\rho_3}{\rho_1} - 0.04. \tag{4.5}$$

The R^2 is 0.96, which shows a very strong correlation. This means that such a regression model is very accurate in estimating local road VMT for networks with medium connectivity ($0.5 < CNR \leq 0.9$). The relative error under this condition is also given in Table 4.6 with an average value of 12.04%, which is quite good.

Table 4.6: Local VMT Estimates for Medium CNR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
6	0.1039	0.1017	2.13%
7	0.1149	0.0981	14.65%
8	0.1233	0.0965	21.72%
9	0.1199	0.1430	19.26%
10	0.1305	0.1532	17.44%
12	0.3851	0.3697	4.02%
14	0.2038	0.2193	7.59%
		Average Error=	12.40%

4.3.1.3 Neighborhoods of High Connectivity

For networks with high connectivity ($0.9 < CNR \leq 1.0$), the format of the regression model will use the 22 (ID=$1 \rightarrow 5, 11, 15 \rightarrow 30$) example networks as shown in Table 4.4.

$$\frac{VMT_L}{VMT_C} = 0.52\frac{\rho_3}{\rho_2} + 1.74\frac{\rho_3}{\rho_1} - 0.01. \tag{4.6}$$

R^2 of this regression equation is 0.48. The real VMT ratio and the ratio calculated based on the regression model are compared in Table 4.7. The errors in the table are calculated based on Equation 4.4. Figure 4.7 is the residual plot. The points in the plot are dispersed quite evenly around the horizontal axis, which indicates that the proposed linear regression model is appropriate for the data.

The average relative error is 19.23%, which is quite good. Although most high connectivity networks are in a grid network ($CNP = 1$), others can have different patterns (e.g., Network 15, 29, 30). So, there is still some error when applying such a linear regression model to local networks with high connectivity. However, the error is within the acceptable range. Figure 4.8 shows the relative error between actual and estimated VMT ratio of both local VMT and collector VMT.

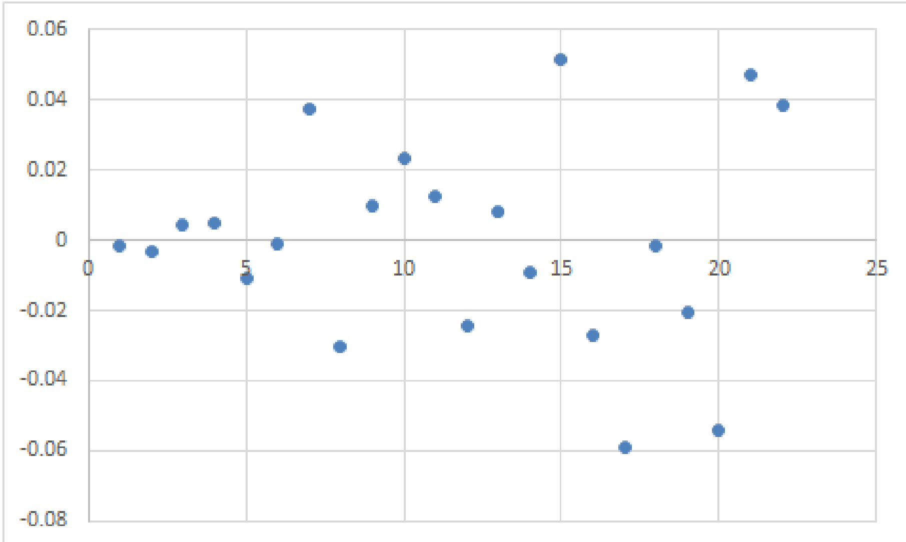


Figure 4.7: Residual Plot Between Real Ratio and Model Result

4.3.2 Collector Road VMT vs. Minor Arterial Road VMT

In Figure 4.2, there are $2 \times 3 = 6$ different combinations of collector-minor arterial networks and minor arterial-principal arterial networks; furthermore, the initial 30 local networks were analyzed under each combination (five local networks under each combination), which generates the VMT and density data in Table 4.1. Moreover, the five additional local networks are analyzed under five of the six combinations. Figure 4.9 shows the detailed classifications of local networks under these six combinations.

In this section, the connectivity level still refers to the 35 local networks, so the classifications are still the same. The only difference is that the author added the minor arterial VMT, which are still traveled (640 demand units) from the same local network.

Following the same procedure, the author first assumes the ratio of collector road VMT and minor arterial road VMT can be represented by the following regression

Table 4.7: Local VMT Estimates for High CNR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
1	0.0995	0.0981	1.36%
2	0.0906	0.0872	3.70%
3	0.0761	0.0807	6.07%
4	0.0628	0.0732	16.59%
5	0.0930	0.0822	11.63%
11	0.1764	0.1754	0.61%
15	0.1278	0.1649	28.97%
16	0.1506	0.1205	19.99%
17	0.1081	0.1180	9.15%
18	0.0926	0.1159	25.23%
19	0.1034	0.1157	11.95%
20	0.1419	0.1175	17.21%
21	0.1425	0.1507	5.74%
22	0.1608	0.1514	5.82%
23	0.0970	0.1484	53.03%
24	0.1794	0.1522	15.17%
25	0.2119	0.1530	27.79%
26	0.1167	0.1151	1.33%
27	0.1366	0.1162	14.94%
28	0.1714	0.1173	31.56%
29	0.0686	0.1157	68.56%
30	0.0821	0.1204	46.63%
		Average Error=	19.23%

model

$$\frac{VMT_C}{VMT_{MA}} = \alpha_1 \frac{\rho_4}{\rho_3} + \alpha_2 \frac{\rho_4}{\rho_2} + \alpha_0. \tag{4.7}$$

4.3.2.1 Neighborhoods of Low Connectivity

The regression model for the six networks (ID=13, 31, 32, 33, 34, 35) with low connectivity was obtained as follows.

$$\frac{VMT_C}{VMT_{MA}} = -0.07 \frac{\rho_4}{\rho_3} + 1.54 \frac{\rho_4}{\rho_2} + 0.06. \tag{4.8}$$

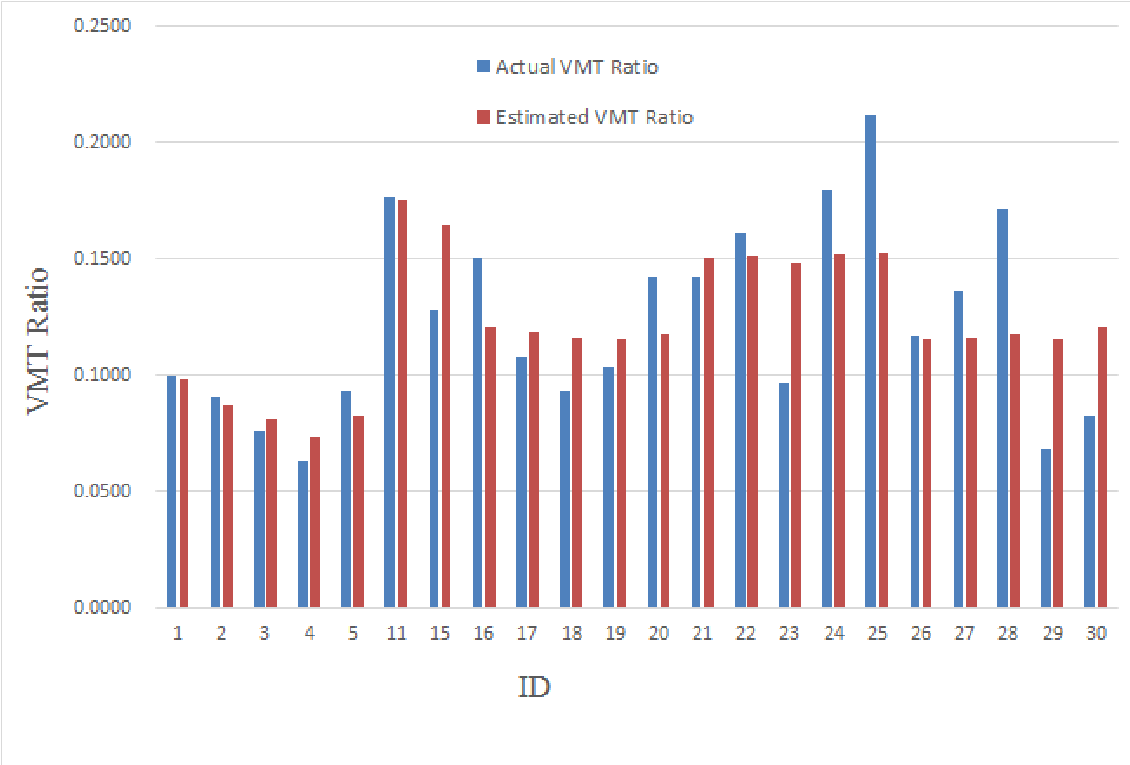


Figure 4.8: VMT Ratio Estimates by Density Ratio Method for High CNR Networks

The R^2 value is 0.96 and average relative error is only 2.99% (shown in Table 4.8), which indicates a strong correlation between the VMT ratio and the key terms.

Table 4.8: Collector VMT Estimates for Low CNR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
13	0.1013	0.0998	1.49%
31	0.0961	0.0961	0.05%
32	0.0665	0.0645	2.93%
33	0.0939	0.0998	6.27%
34	0.1045	0.1002	4.20%
35	0.0626	0.0645	3.03%
		Average Error=	2.99%

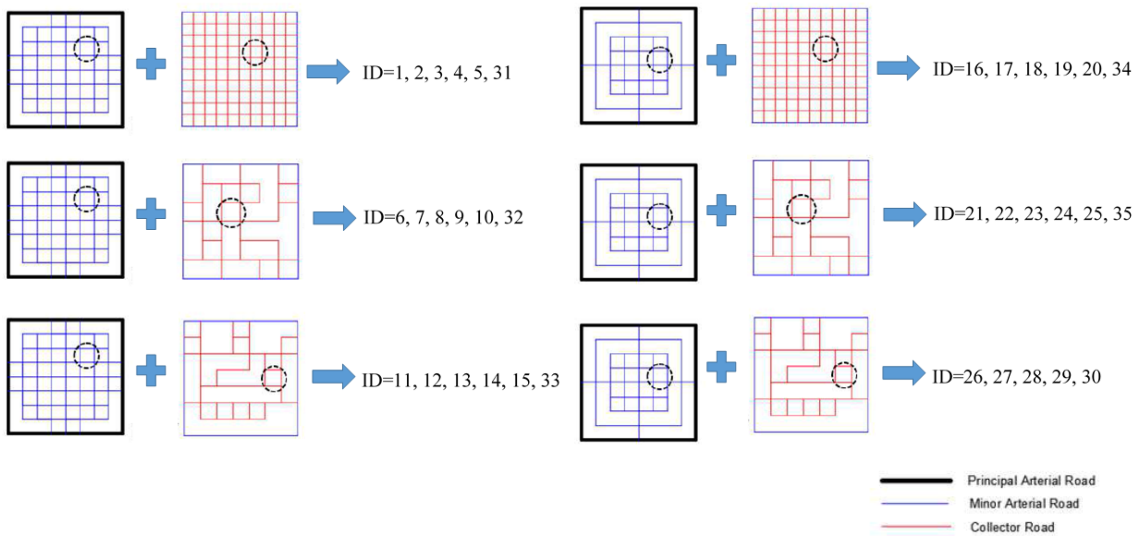


Figure 4.9: Local Network Classifications under Higher Layered Classes of Roadways

4.3.2.2 Neighborhoods of Medium Connectivity

Using the seven example local networks (ID=6, 7, 8, 9, 10, 12, 14), the format of the regression model is as follows.

$$\frac{VMT_C}{VMT_{MA}} = -0.53\frac{\rho_4}{\rho_3} + 0.18. \tag{4.9}$$

The R^2 for this regression model is 0.98 with an average relative error of 1.96% (shown in Table 4.9). Since the value of the term $\frac{\rho_4}{\rho_2}$ is much smaller compared with $\frac{\rho_4}{\rho_3}$, the missing value of this term has very little impact on the accuracy of the linear regression model.

Table 4.9: Collector VMT Estimates for Medium CNR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
6	0.0631	0.0634	0.40%
7	0.0627	0.0634	1.03%
8	0.0626	0.0634	1.29%
9	0.0620	0.0634	2.26%
10	0.0665	0.0634	4.67%
12	0.0912	0.0931	2.09%
14	0.0950	0.0931	2.01%
			1.96%

4.3.2.3 Neighborhoods of High Connectivity

Using the 22 (ID=1 $\rightarrow 5, 11, 15 \rightarrow 30$) example networks, the linear regression model for high connectivity networks is as follows.

$$\frac{VMT_C}{VMT_{MA}} = -0.33\frac{\rho_4}{\rho_3} + 1.6\frac{\rho_4}{\rho_2} + 0.15. \tag{4.10}$$

The R^2 is 0.87 for this regression model, which also shows that the regression model is able to estimate the VMT ratio data accurately. The average error is only 4.25% as shown in Table 4.10.

In conclusion, the relationship between the VMT ratio and densities is robust for collector and minor arterial roads for all cases of low, medium, or high connectivity networks.

4.4 Logarithmic Model

An alternative way to characterize the VT ratio is through the use of logarithmic terms of road densities.

Table 4.10: Collector VMT Estimates for High CNR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
1	0.0709	0.0723	1.90%
2	0.0716	0.0723	0.94%
3	0.0728	0.0723	0.65%
4	0.0735	0.0723	1.65%
5	0.0731	0.0723	1.05%
11	0.0964	0.1047	8.60%
15	0.0925	0.1047	13.15%
16	0.0817	0.0863	5.70%
17	0.0827	0.0863	4.34%
18	0.0834	0.0863	3.45%
19	0.0819	0.0863	5.42%
20	0.0831	0.0863	3.81%
21	0.1106	0.1050	5.01%
22	0.1106	0.1050	5.01%
23	0.1029	0.1050	2.08%
24	0.1106	0.1050	5.01%
25	0.1106	0.1050	5.01%
26	0.0894	0.0867	3.03%
27	0.0894	0.0867	3.03%
28	0.0894	0.0867	3.03%
29	0.0926	0.0867	6.37%
30	0.0914	0.0867	5.18%
		Average Error=	4.25%

4.4.1 Local Road VMT vs. Collector Road VMT

The general format of the logarithmic regression model is proposed in Equation 3.4 and shown as follows.

$$ln(VMT_L) = \alpha_1 ln(VMT_C) + \alpha_2 ln\rho_3 + \alpha_3 ln\rho_2 + \alpha_4 ln\rho_1 + \alpha_0$$

where α_n $(n = 0, 1, 2, 3, 4)$ is the coefficient Here the author still considers the impact of ρ_1.

4.4.1.1 Neighborhoods of Low Connectivity

By using the five local network examples (ID=13, 31,32, 33, 34, 35), the regression model for local low connectivity networks is obtained as follows.

$$ln(VMT_L) = 1.96ln(VMT_C) + 4.06ln\rho_3 + 6.93ln\rho_2 - 5.95ln\rho_1 + 15.86. \qquad (4.11)$$

R^2 is 0.26 for this equation. Note that this R^2 is calculated based on the actual and estimated VMT rather than the logarithmic values for the purpose of consistency, which makes the logarithmic regression models comparable with density ratio regression models. All the following R^2 for logarithmic regression models are calculated in this way.

Table 4.11 shows the comparison between the actual VMT and estimated VMT. The error is calculated using a method similar to the density ratio method. The difference is that in this case, the error is calculated based on the VMT data. The equation is as follows:

$$\text{Error}(\%) = \frac{|VMT_L(\text{Model Result}) - VMT_L|}{VMT_L} \times 100\%. \qquad (4.12)$$

According to the results shown in Table 4.11, the average error is 57.72%, which indicates that the regression model is not able to estimate local VMT for low connectivity networks accurately. However, it still generates more accurate results than the density ratio method.

Table 4.11: Local VMT Estimates for Low CNR Networks: Logarithmic Model

ID	$ln(VMT_L)$	$ln(VMT_L)$(Model)	VMT_L	VMT_L(Model)	Error (%)
13	9.5894	9.1342	14608.41	9266.53	36.57%
32	9.5127	8.8839	13530.00	7215.01	46.67%
33	7.7706	7.8379	2370.00	2534.83	6.95%
34	7.9204	8.6574	2753.00	5752.33	108.95%
35	7.9047	8.6472	2710.00	5694.40	110.13%
31	8.2079	7.7452	3670.00	2310.46	37.04%
				Average Error=	57.72%

4.4.1.2 Neighborhoods of Medium Connectivity

The specific regression model was conducted on seven local networks (ID=6, 7, 8, 9, 10, 12, 14) and is presented as follows.

$$ln(VMT_L) = -1.66ln(VMT_C) - 0.01ln\rho_3 - 1.32ln\rho_1 + 23.53. \tag{4.13}$$

The R^2 is 0.76 for this regression model, and the average relative error is 9.43 % according to Table 4.12. This indicates that the regression model is quite accurate within medium connectivity networks.

Table 4.12: Local VMT Estimates for Medium CNR Networks: Logarithmic Model

ID	$ln(VMT_L)$	$ln(VMT_L)$(Model)	VMT_L	VMT_L(Model)	Error (%)
6	7.4419	7.4919	1705.91	1793.49	5.13%
7	7.5366	7.4813	1875.50	1774.60	5.38%
8	7.6041	7.4760	2006.39	1765.19	12.02%
9	7.5671	7.7445	1933.45	2308.72	19.41%
10	7.7215	7.6776	2256.31	2159.54	4.29%
12	8.4640	8.3655	4740.84	4296.08	9.38%
14	7.8685	7.9671	2613.75	2884.61	10.36%
				Average Error=	9.43%

4.4.1.3 Neighborhoods of High Connectivity

The format of the regression model is as follows using the 22 (ID=1 $\rightarrow 5, 11, 15 \rightarrow$ 30) example networks as shown in Table 4.4.

$$ln(VMT_L) = 1.12ln(VMT_C) + 0.89ln\rho_3 - 0.63ln\rho_2 - 0.48ln\rho_1 - 1.00. \qquad (4.14)$$

The R^2 for this model is 0.47 and the specific comparison is shown in Table 4.13. Figure 4.10 is the residual plot. Based on the plot, the points are still quite evenly distributed around the horizontal axis. So, even when the R^2 seems poor, the proposed liner regression model is appropriate for the data.

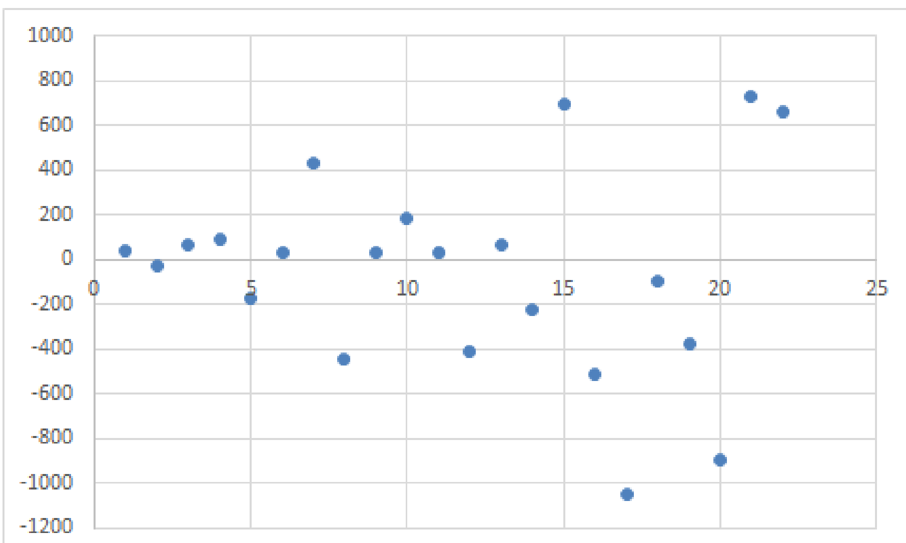


Figure 4.10: Residual Plot Between Actual and Modeled Local VMT Data

According to the results shown in the table, the average relative error of this model is 17.24%, which indicates that the regression model is still quite robust for estimating

Table 4.13: Local VMT Estimates for High CNR Networks: Logarithmic Model

ID	$ln(VMT_L)$	$ln(VMT_L)$(Model)	VMT_L	VMT_L(Model)	Error (%)
1	7.3758	7.4000	1596.90	1636.01	2.39%
2	7.2917	7.2740	1468.07	1442.32	1.79%
3	7.1332	7.1858	1252.86	1320.60	5.13%
4	6.9517	7.0373	1044.92	1138.32	8.21%
5	7.3377	7.2161	1537.15	1361.12	12.93%
11	7.7389	7.7538	2295.96	2330.36	1.48%
15	7.3757	7.6131	1596.70	2024.50	21.13%
16	7.5543	7.2868	1908.87	1460.94	30.66%
17	7.2362	7.2605	1388.79	1422.90	2.40%
18	7.0895	7.2322	1199.35	1383.24	13.29%
19	7.1807	7.2064	1313.84	1348.10	2.54%
20	7.5132	7.2569	1832.15	1417.81	29.22%
21	7.8090	7.8365	2462.78	2531.32	2.71%
22	7.9297	7.8470	2778.49	2558.10	8.62%
23	7.3518	7.7209	1559.06	2254.90	30.86%
24	8.0393	7.8578	3100.33	2585.79	19.90%
25	8.2056	7.8688	3661.29	2614.48	40.04%
26	7.5369	7.4858	1876.07	1782.60	5.24%
27	7.6944	7.5065	2196.07	1819.77	20.68%
28	7.9217	7.5279	2756.47	1859.25	48.26%
29	7.0412	7.5359	1142.77	1874.12	39.02%
30	7.2082	7.6066	1350.51	2011.41	32.86%
				Average Error=	17.24%

local VMT with high connectivity networks. Figure 4.11 shows the relative error between actual VMT and estimated VMT.

4.4.2 Collector Road VMT vs. Minor Arterial Road VMT

The general format of the logarithmic regression model between collector road VMT and minor arterial road VMT is introduced in Equation 3.6 and shown as follows.

$$ln(VMT_C) = \alpha_1 ln(VMT_{MA}) + \alpha_2 ln\rho_4 + \alpha_3 ln\rho_3 + \alpha_4 ln\rho_2 + \alpha_0$$

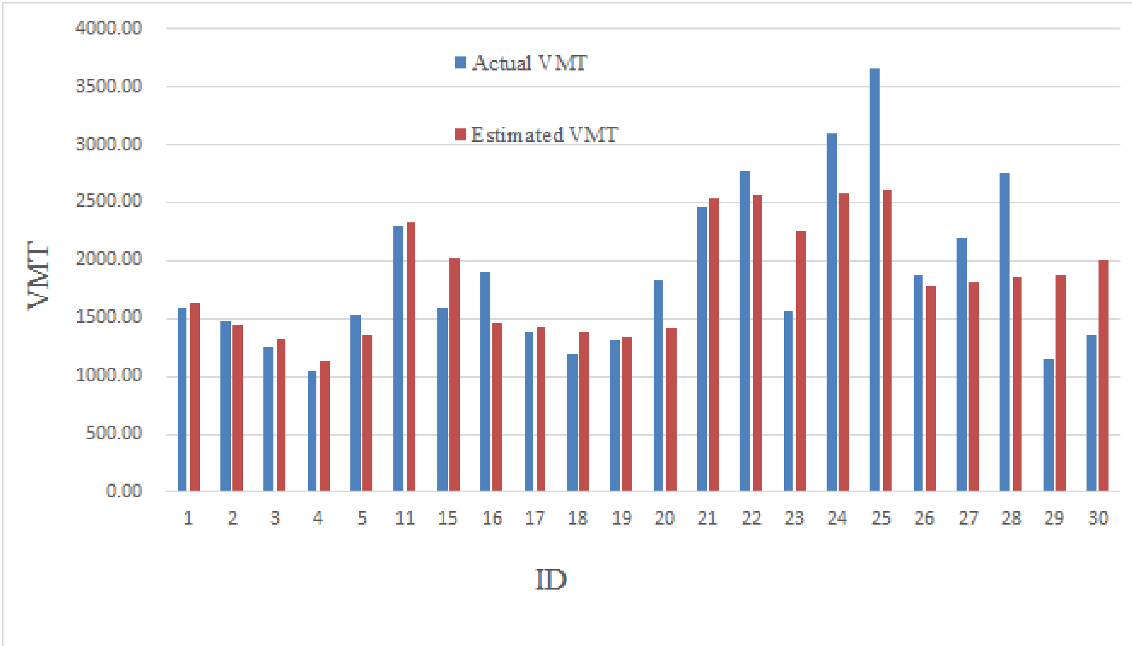


Figure 4.11: VMT Estimation by Logarithmic Method for High CNR Networks

where α_n $(n = 0, 1, 2, 3, 4)$ is the coefficient. Here the author still considers the impact of ρ_2.

As clarified before, the connectivity level still refers to the 35 local networks, so the classifications are still the same. The only difference is that the author adds the minor arterial VMT which are still traveled (640 demand units) from the same local network.

4.4.2.1 Neighborhoods of Low Connectivity

Using the six low connectivity local networks (ID=13, 31, 32, 33, 34, 35) as examples, the regression model was obtained from a previous analysis and shown as follows.

$$ln(VMT_C) = -17.27ln(VMT_{MA}) - 9.11ln\rho_4 - 8.65ln\rho_3 + 135.54. \qquad (4.15)$$

This regression model has an R^2 of 0.95 with an average relative error of 2.26% (shown in Table 4.14), which shows that the logarithmic regression model to be a very reasonable method for estimating collector road VMT for low connectivity networks.

Table 4.14: Collector VMT Estimates for Low CNR Networks: Logarithmic Model

ID	$ln(VMT_C)$	$ln(VMT_C)$(Model)	VMT_C	VMT_C(Model)	Error (%)
13	9.5236	9.4857	13678.66	13169.87	3.72%
32	9.7582	9.7284	17294.65	16787.21	2.93%
33	9.4478	9.4857	12680.00	13169.87	3.86%
34	9.7011	9.7011	16335.00	16335.00	0.00%
35	9.6986	9.7284	16294.65	16787.21	3.02%
31	9.7573	9.7573	17280.00	17280.00	0.00%
				Average Error=	2.26%

4.4.2.2 Neighborhoods of Medium Connectivity

Using the seven medium connectivity local networks (ID=6, 7, 8, 9, 10, 12, 14) as examples, the final format of the logarithmic regression model is shown in Equation 4.16.

$$ln(VMT_C) = ln(VMT_{MA}) + 0.48ln\rho_3 - 0.71. \tag{4.16}$$

The R^2 for this regression model is 0.96 and the relative error is 1.95% as shown in Table 4.15. The term $ln\rho_4$ is not included, because this variable is not significant according to statistical test result. So it is removed from the proposed regression equation. This might indicate that for medium connectivity networks, the density of minor arterial roads is the most important factor in estimating the collector road VMT if the minor arterial road VMT is given.

Table 4.15: Collector VMT Estimates for Medium CNR Networks: Logarithmic Model

ID	$ln(VMT_C)$	$ln(VMT_C)$(Model)	VMT_C	VMT_C(Model)	Error (%)
6	9.7063	9.7100	16420.99	16480.92	0.36%
7	9.7000	9.7100	16317.83	16480.92	1.00%
8	9.6975	9.7100	16276.20	16480.92	1.26%
9	9.6880	9.7100	16122.20	16480.92	2.22%
10	9.7581	9.7100	17293.29	16480.92	4.70%
12	9.4182	9.4387	12310.20	12565.34	2.07%
14	9.4592	9.4387	12825.87	12565.34	2.03%
				Average Error=	1.95%

4.4.2.3 Neighborhoods of High Connectivity

Using the 22 (ID=1 $\rightarrow 5, 11, 15 \rightarrow 30$) example networks, the regression model for high connectivity networks is as follows.

$$ln(VMT_C) = -49.22ln(VMT_{MA}) - 25.59ln\rho_4 - 23.95ln\rho_3 + +0.96ln\rho_2 + 375.11. \tag{4.17}$$

The R^2 is 0.97 with an average relative error of 1.48% as shown in Table 4.16. It shows that the regression model is accurate in estimating the collector road VMT for high connectivity roads as well.

4.5 Comparison of the Two Estimation Methods

Figure 4.12 shows the average errors of the two proposed methods (density ratio method and logarithmic method) estimating VMT under different situations. Accoridng to this figure, the average errors are less than 20% for both methods under most situations (except in the case of a local VMT estimation for low CNR networks).

Moreover, the logarithmic method shows better performance estimating both

Table 4.16: Collector VMT Estimates for High CNR Networks: Logarithmic Model

ID	$ln(VMT_C)$	$ln(VMT_C)$(Model)	VMT_C	VMT_C(Model)	Error (%)
1	9.6837	9.7040	16054.02	16383.67	2.05%
2	9.6932	9.7040	16206.90	16383.67	1.09%
3	9.7091	9.7040	16467.47	16383.67	0.51%
4	9.7192	9.7040	16634.29	16383.67	1.51%
5	9.7132	9.7040	16534.01	16383.67	0.91%
11	9.4737	9.4535	13013.15	12753.35	2.00%
15	9.4327	9.4535	12490.54	12753.35	2.10%
16	9.4477	9.4591	12678.84	12823.79	1.14%
17	9.4607	9.4591	12844.47	12823.79	0.16%
18	9.4692	9.4591	12954.54	12823.79	1.01%
19	9.4503	9.4591	12712.41	12823.79	0.88%
20	9.4658	9.4591	12910.06	12823.79	0.67%
21	9.7572	9.7432	17278.63	17037.29	1.40%
22	9.7572	9.7432	17278.63	17037.29	1.40%
23	9.6852	9.7432	16078.23	17037.29	5.96%
24	9.7572	9.7432	17278.63	17037.29	1.40%
25	9.7572	9.7432	17278.63	17037.29	1.40%
26	9.6852	9.6971	16078.23	16269.74	1.19%
27	9.6852	9.6971	16078.23	16269.74	1.19%
28	9.6852	9.6971	16078.23	16269.74	1.19%
29	9.7203	9.6971	16651.91	16269.74	2.30%
30	9.7077	9.6971	16443.75	16269.74	1.06%
				Average Error=	1.48%

local and collector VMT with smaller average errors. The difference between average errors of the two methods estimating low CNR for local VMT is very conspicuous. However, for other situations, the average errors of the two methods are very close to each other.

Overall, the two methods are both robust in estimating local and collector VMT under most situations except for estimating local VMT on low CNR networks. This indicates one of the possible weaknesses of the proposed methods.

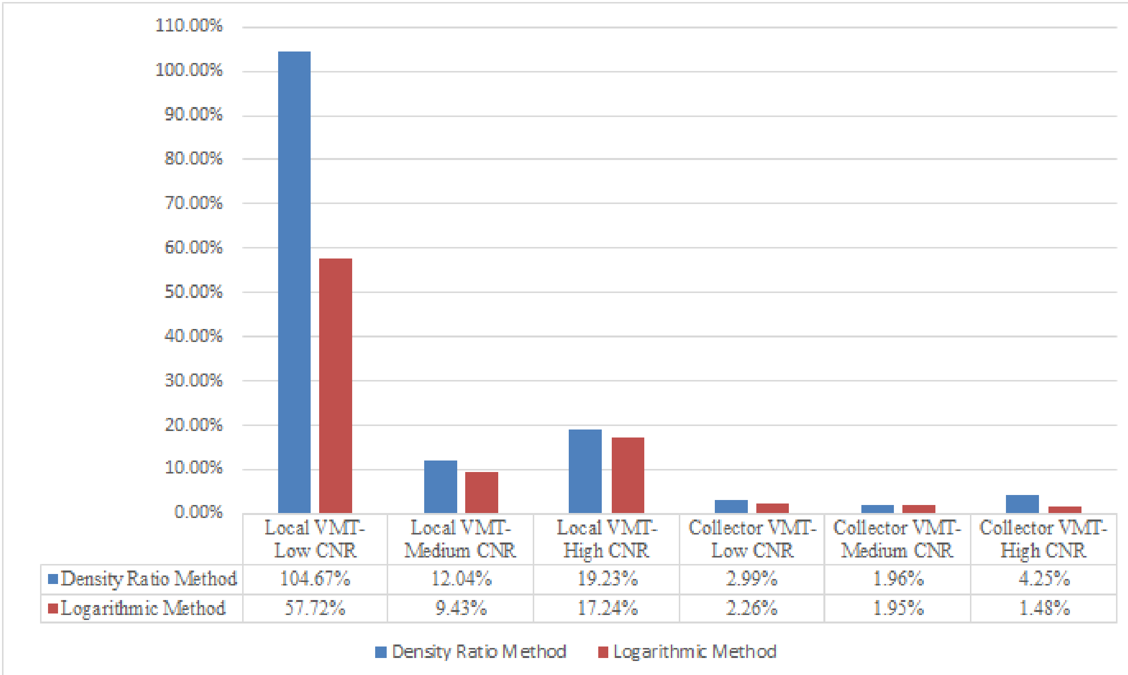


Figure 4.12: Average Errors of the Two Estimation Methods

4.6 Link-Node Ratio Measure

The second connectivity measure used to divide the local networks is called the Link-Node Ratio (LNR). It is measured as the number of links divided by the number of nodes with a study area. The nodes include all the real and dangle nodes. A higher number of LNR shows that a certain network is more connected. The equation is expressed as follows.

$$LNR = \frac{\#\text{ Links}}{\#\text{ Total Nodes}}. \tag{4.18}$$

A reasonable Link-Node Ratio is considered to be at least 1.4, so the author divides all 35 local networks into three intervals: low connectivity with $LNR \in (0, 1.4]$, medium connectivity with $LNR \in (1.4, 2.0]$, high connectivity with $LNR \in (2.0, \infty)$. Table 4.17 shows the results of the Link-Node Ratio for 35 local networks and specific classification results are given in Table 4.18.

Compared with the classification of the CNR method, some of the communities have switched to a different categorization, including ID=5, 8, 10, 12, 14, 21, 22, and 24 $\rightarrow$ 30.

4.6.1 Density Ratio Model

4.6.1.1 Local Road VMT vs. Collector Road VMT

Following the same procedure, the regression equations for the three different intervals are listed as follows. The low LNR interval includes 10 example networks (ID=$8, 10, 12 \rightarrow 14, 31 \rightarrow 35$), the medium LNR interval includes 14 example networks (ID=$5, 6, 7, 9, 16, 21, 22, 24 \rightarrow 30$), and the high LNR interval includes 11 example networks (ID=$1 \rightarrow 4, 11, 15, 17 \rightarrow 20, 23$).

$$\frac{VMT_L}{VMT_C} = \begin{cases} -5.93\frac{\rho_3}{\rho_2} + 42.58\frac{\rho_3}{\rho_1} - 0.07, & LNR \in (0, 1.4] \\ 0.20\frac{\rho_3}{\rho_2} + 8.57\frac{\rho_3}{\rho_1} - 0.04, & LNR \in (1.4, 2.0] \\ 0.28\frac{\rho_3}{\rho_2} + 2.50\frac{\rho_3}{\rho_1} + 0.02. & LNR \in (2.0, \infty) \end{cases}$$

The R^2 for the three intervals are 0.20, 0.48, and 0.70, respectively. Specific comparison results are shown in Table 4.19, Table 4.20, and Table 4.21. The average relative error for the first interval is 71.92%, which indicates the density ratio model is not very accurate estimating local VMT of networks with small LNR. However, for the networks in the other two intervals, the density ratio model worked better.

4.6.1.2 Collector Road VMT vs. Minor Arterial Road VMT

The regression equations for estimating collector road VMT are obtained and shown as follows.

Table 4.17: Link-Node Ratio of 35 Networks: LNR

ID	Link #	Real Node #	Dangle Node #	LNR
1	24	9	0	2.67
2	40	16	0	2.50
3	60	25	0	2.40
4	112	49	0	2.29
5	45	23	0	1.96
6	37	19	3	1.68
7	41	21	5	1.58
8	59	27	24	1.16
9	35	18	3	1.67
10	16	8	4	1.33
11	24	12	0	2.00
12	18	9	4	1.38
13	1	0	1	1.00
14	35	20	6	1.35
15	52	25	0	2.08
16	84	45	0	1.87
17	92	45	0	2.04
18	100	45	0	2.22
19	105	49	0	2.14
20	97	48	0	2.02
21	89	47	0	1.89
22	85	45	0	1.89
23	98	49	0	2.00
24	83	45	0	1.84
25	81	45	0	1.80
26	89	45	0	1.98
27	86	45	0	1.91
28	82	45	0	1.82
29	85	43	0	1.98
30	61	32	1	1.85
31	27	10	16	1.04
32	1	0	1	1.00
33	58	28	28	1.04
34	30	12	16	1.07
35	22	7	14	1.05

Table 4.18: Network Classifications: LNR

$LNR \in (0, 1.4]$		$LNR \in (1.4, 2.0]$		$LNR \in (2.0, \infty)$	
ID	LNR	ID	LNR	ID	LNR
8	1.16	5	1.96	1	2.67
10	1.33	6	1.68	2	2.50
12	1.38	7	1.58	3	2.40
13	1.00	9	1.67	4	2.29
14	1.35	16	1.87	11	2.00
31	1.04	21	1.89	15	2.08
32	1.00	22	1.89	17	2.04
33	1.04	24	1.84	18	2.22
34	1.07	25	1.80	19	2.14
35	1.05	26	1.98	20	2.02
		27	1.91	23	2.00
		28	1.82		
		29	1.98		
		30	1.85		

Table 4.19: Local VMT Estimates for Low LNR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
8	0.1233	0.1603	30.07%
10	0.1305	0.3143	140.86%
12	0.3851	0.5649	46.67%
13	1.0680	0.4992	53.26%
14	0.2038	0.1568	23.06%
31	0.2124	0.3843	80.94%
32	0.7823	0.3429	56.17%
33	0.1869	0.1865	0.19%
34	0.1685	0.4907	191.16%
35	0.1663	0.3273	96.77%
		Average Error=	71.92%

$$\frac{VMT_C}{VMT_{MA}} = \begin{cases} -0.02\frac{\rho_4}{\rho_3} + 1.55\frac{\rho_4}{\rho_2} + 0.05, & LNR \in (0, 1.4] \\ -0.34\frac{\rho_4}{\rho_3} + 1.45\frac{\rho_4}{\rho_2} + 0.11, & DR \in (1.4, 2.0] \\ -0.26\frac{\rho_4}{\rho_3} + 1.24\frac{\rho_4}{\rho_2} + 0.10. & DR \in (2.0, \infty) \end{cases}$$

Table 4.20: Local VMT Estimates for Medium LNR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
5	0.0930	0.1149	23.59%
6	0.1039	0.0984	5.28%
7	0.1149	0.0964	16.08%
9	0.1199	0.1210	0.88%
16	0.1506	0.1394	7.43%
21	0.1425	0.1654	16.02%
22	0.1608	0.1690	5.08%
24	0.1794	0.1728	3.72%
25	0.2119	0.1767	16.60%
26	0.1167	0.1107	5.09%
27	0.1366	0.1159	15.12%
28	0.1714	0.1216	29.08%
29	0.0686	0.1134	65.28%
30	0.0821	0.1368	66.61%
		Average Error=	19.70%

Table 4.21: Local VMT Estimates for High LNR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
1	0.0995	0.1061	6.70%
2	0.0906	0.0905	0.08%
3	0.0761	0.0811	6.65%
4	0.0628	0.0704	12.11%
11	0.1764	0.1605	9.05%
15	0.1278	0.1454	13.74%
17	0.1081	0.1020	5.65%
18	0.0926	0.0990	6.96%
19	0.1034	0.0987	4.52%
20	0.1419	0.1013	28.65%
23	0.0970	0.1211	24.91%
		Average Error=	10.82%

The R^2 for the above three regression equations are 0.95, 0.97, and 0.95, respectively. The results show that the proposed regression model is very accurate in estimating the collector road VMT given the minor arterial road VMT. The average relative errors for the three intervals are calculated and shown in Table 4.22, Table 4.23, and Table 4.24.

Table 4.22: Collector VMT Estimates for Low LNR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
8	0.0626	0.0645	3.12%
10	0.0665	0.0645	2.94%
12	0.0912	0.0971	6.52%
13	0.1013	0.0971	4.14%
14	0.0950	0.0971	2.23%
31	0.0961	0.0961	0.08%
32	0.0665	0.0645	2.95%
33	0.0939	0.0971	3.41%
34	0.1045	0.0975	6.77%
35	0.0626	0.0645	3.01%
		Average Error=	3.52%

4.6.2 Logarithmic Model

4.6.2.1 Local Road VMT vs. Collector Road VMT

Then, the logarithmic model was used to develop the regression equations for the three intervals which are shown as follows. As with the density ratio method, the low LNR interval includes 10 example networks (ID=$8, 10, 12 \rightarrow 14, 31 \rightarrow 35$); the medium LNR interval includes 14 example networks (ID=$5, 6, 7, 9, 16, 21, 22, 24 \rightarrow 30$), and the high LNR interval includes 11 example networks (ID=$1 \rightarrow 4, 11, 15, 17 \rightarrow 20, 23$).

Table 4.23: Collector VMT Estimates for Medium LNR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
5	0.0731	0.0794	8.67%
6	0.0631	0.0605	4.21%
7	0.0627	0.0605	3.60%
9	0.0620	0.0605	2.43%
16	0.0817	0.0898	9.93%
21	0.1106	0.1090	1.43%
22	0.1106	0.1090	1.43%
24	0.1106	0.1090	1.43%
25	0.1106	0.1090	1.43%
26	0.0894	0.0901	0.79%
27	0.0894	0.0901	0.79%
28	0.0894	0.0901	0.79%
29	0.0926	0.0901	2.68%
30	0.0914	0.0901	1.45%
		Average Error=	2.93%

Table 4.24: Collector VMT Estimates for High LNR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
1	0.0709	0.0722	1.76%
2	0.0716	0.0722	0.80%
3	0.0728	0.0722	0.79%
4	0.0735	0.0722	1.79%
11	0.0964	0.0972	0.84%
15	0.0925	0.0972	5.06%
17	0.0827	0.0828	0.08%
18	0.0834	0.0828	0.77%
19	0.0819	0.0828	1.12%
20	0.0831	0.0828	0.42%
23	0.1029	0.0975	5.27%
		Average Error=	1.70%

$$ln(VMT_L) = \begin{cases} 3.64ln(VMT_C) + 3.90ln\rho_3 + 5.35ln\rho_2 - 3.51ln\rho_1 - 3.28, & LNR \in (0, 1.4] \\ 0.43ln(VMT_C) + 1.37ln\rho_3 - 0.14ln\rho_2 - 1.24ln\rho_1 + 8.81, & LNR \in (1.4, 2.0] \\ -0.02ln(VMT_C) + 0.19ln\rho_3 - 0.54ln\rho_2 - 0.60ln\rho_1 + 7.37. & LNR \in (2.0, \infty) \end{cases}$$

The R^2 of the regression equation for the first interval is 0.41 with an average relative error of 45.92% (as shown in Table 4.25); hence, this logarithmic regression model does not fit the networks very well with a small LNR. The R^2 for the other two intervals are 0.48 and 0.74. Specific results are shown in Table 4.26 and Table 4.27. The average relative errors of these two intervals are only 18.98% and 7.61%, respectively.

Table 4.25: Local VMT Estimates for Low LNR Networks: Logarithmic Model

ID	$ln(VMT_L)$	$ln(VMT_L)$(Model)	VMT_L	VMT_L(Model)	Error (%)
8	7.6041	7.4507	2006.39	1720.98	14.22%
10	7.7215	8.4746	2256.31	4791.66	112.37%
12	8.4640	8.6248	4740.84	5568.22	17.45%
13	9.5894	8.8818	14608.41	7200.08	50.71%
14	7.8685	7.8969	2613.75	2689.06	2.88%
31	8.2079	7.7764	3670.00	2383.74	35.05%
32	9.5127	8.6060	13530.00	5464.50	59.61%
33	7.7706	7.9272	2370.00	2771.66	16.95%
34	7.9204	8.6077	2753.00	5473.74	98.83%
35	7.9047	8.3179	2710.00	4096.52	51.16%
				Average Error=	45.92%

4.6.2.2 Collector Road VMT vs. Minor Arterial Road VMT

Using the same example networks for each interval, the regression equations used to estimate collector road VMT are listed below.

$$ln(VMT_C) = \begin{cases} 1.00ln(VMT_{MA}) - 0.20ln\rho_4 + 0.29ln\rho_3 - 0.67ln\rho_2 - 3.64, & LNR \in (0, 1.4] \\ -25.15ln(VMT_{MA}) - 13.67ln\rho_4 - 12.11ln\rho_3 + 0.14ln\rho_2 + 193.02, & LNR \in (1.4, 2.0] \\ 1.00ln(VMT_{MA}) - 0.39ln\rho_4 + 0.46ln\rho_3 - 0.60ln\rho_2 - 3.94. & LNR \in (2.0, \infty) \end{cases}$$

Table 4.26: Local VMT Estimates for Medium LNR Networks: Logarithmic Model

ID	$ln(VMT_L)$	$ln(VMT_L)$(Model)	VMT_L	VMT_L(Model)	Error (%)
5	7.3377	7.5407	1537.15	1883.06	22.50%
6	7.4419	7.3839	1705.91	1609.92	5.63%
7	7.5366	7.3615	1875.50	1574.21	16.06%
9	7.5671	7.5843	1933.45	1967.00	1.74%
16	7.5543	7.5980	1908.87	1994.20	4.47%
21	7.8090	7.8934	2462.78	2679.66	8.81%
22	7.9297	7.9209	2778.49	2754.29	0.87%
24	8.0393	7.9490	3100.33	2832.78	8.63%
25	8.2056	7.9778	3661.29	2915.57	20.37%
26	7.5369	7.4296	1876.07	1685.08	10.18%
27	7.6944	7.4834	2196.07	1778.34	19.02%
28	7.9217	7.5395	2756.47	1880.83	31.77%
29	7.0412	7.4727	1142.77	1759.42	53.96%
30	7.2082	7.6887	1350.51	2183.47	61.68%
				Average Error=	18.98%

Table 4.27: Local VMT Estimates for High LNR Networks: Logarithmic Model

ID	$ln(VMT_L)$	$ln(VMT_L)$(Model)	VMT_L	VMT_L(Model)	Error (%)
1	7.3758	7.4385	1596.90	1700.25	6.47%
2	7.2917	7.2651	1468.07	1429.49	2.63%
3	7.1332	7.1303	1252.86	1249.26	0.29%
4	6.9517	6.9274	1044.92	1019.84	2.40%
11	7.7389	7.6156	2295.96	2029.64	11.60%
15	7.3757	7.4961	1596.70	1800.95	12.79%
17	7.2362	7.2767	1388.79	1446.16	4.13%
18	7.0895	7.2285	1199.35	1378.21	14.91%
19	7.1807	7.2230	1313.84	1370.63	4.32%
20	7.5132	7.2648	1832.15	1429.10	22.00%
23	7.3518	7.3729	1559.06	1592.31	2.13%
				Average Error=	7.61%

The R^2 for these three intervals are 0.98, 0.98, and 0.99, respectively. It shows that the logarithmic regression model works well for all 35 networks when estimating collector road VMT given minor arterial road VMT. The average relative errors of all three intervals are also given (shown in Table 4.28, Table 4.29, and Table 4.30).

Table 4.28: Collector VMT Estimates for Low LNR Networks: Logarithmic Model

ID	$ln(VMT_L)$	$ln(VMT_L)$(Model)	VMT_L	VMT_L(Model)	Error (%)
8	9.6975	9.7281	16276.20	16782.65	3.11%
10	9.7581	9.7281	17293.29	16782.65	2.95%
12	9.4182	9.4622	12310.20	12864.47	4.50%
13	9.5236	9.4622	13678.66	12864.47	5.95%
14	9.4592	9.4622	12825.87	12864.47	0.30%
31	9.7573	9.7573	17280.00	17280.55	0.00%
32	9.7582	9.7281	17294.65	16782.65	2.96%
33	9.4478	9.4622	12680.00	12864.47	1.45%
34	9.7011	9.7011	16335.00	16335.52	0.00%
35	9.6986	9.7281	16294.65	16782.65	2.99%
				Average Error=	2.42%

4.7 Distance Ratio Measure

The author also defines another geographic measure called distance ratio as well. Distance Ratio (DR) is calculated based on the following equation.

$$DR = \frac{\text{Avg Assumed Travel Distance}}{\text{Avg Actual Travel Distance}}. \tag{4.19}$$

This measurement shows how well the model assumption performs when estimating the actual local distance traveled within a local network, so it is actually used to test the proposed models– not for connectivity purpose.

From previous analysis, the average assumed local distance traveled is $\frac{L}{6} + \frac{d}{4}$. For all the 35 local networks, L is equal to 8 according to the simulation setting. d is

Table 4.29: Collector VMT Estimates for Medium LNR Networks: Logarithmic Model

ID	$ln(VMT_L)$	$ln(VMT_L)$(Model)	VMT_L	VMT_L(Model)	Error (%)
5	9.7132	9.7137	16534.01	16542.18	0.05%
6	9.7063	9.6986	16420.99	16294.55	0.77%
7	9.7000	9.6986	16317.83	16294.55	0.14%
9	9.6880	9.6986	16122.20	16294.55	1.07%
16	9.4477	9.4482	12678.84	12684.87	0.05%
21	9.7572	9.7577	17278.63	17286.95	0.05%
22	9.7572	9.7577	17278.63	17286.95	0.05%
24	9.7572	9.7577	17278.63	17286.95	0.05%
25	9.7572	9.7577	17278.63	17286.95	0.05%
26	9.6852	9.6972	16078.23	16272.13	1.21%
27	9.6852	9.6972	16078.23	16272.13	1.21%
28	9.6852	9.6972	16078.23	16272.13	1.21%
29	9.7203	9.6972	16651.91	16272.13	2.28%
30	9.7077	9.6972	16443.75	16272.13	1.04%
				Average Error=	0.66%

Table 4.30: Collector VMT Estimates for High LNR Networks: Logarithmic Model

ID	$ln(VMT_L)$	$ln(VMT_L)$(Model)	VMT_L	VMT_L(Model)	Error (%)
1	9.6837	9.7013	16054.02	16339.08	1.78%
2	9.6932	9.7013	16206.90	16339.08	0.82%
3	9.7091	9.7013	16467.47	16339.08	0.78%
4	9.7192	9.7013	16634.29	16339.08	1.77%
11	9.4737	9.4532	13013.15	12749.12	2.03%
15	9.4327	9.4532	12490.54	12749.12	2.07%
17	9.4607	9.4615	12844.47	12855.00	0.08%
18	9.4692	9.4615	12954.54	12855.00	0.77%
19	9.4503	9.4615	12712.41	12855.00	1.12%
20	9.4658	9.4615	12910.06	12855.00	0.43%
23	9.6852	9.6852	16078.23	16078.17	0.00%
				Average Error=	1.06%

easy to obtain for grid networks (ID=1, 2, 3, 4) rather than for other networks. So, according to the definition of local road density (ρ_1), an equation can be found to represent d in non-grid networks. Equation 4.20 shows the result.

$$\begin{aligned} \rho_1 = \frac{2}{d} &= \frac{\text{Total Local Road Length}}{\text{Area}} \\ \Longrightarrow \frac{2}{d} &= \frac{\text{Total Local Road Length}}{64} \\ \Longrightarrow d &= \frac{128}{\text{Total Local Road Length}}. \end{aligned} \tag{4.20}$$

Table 4.31 shows the Distance Ratio Results for all 35 local networks.

The average actual travel distance is calculated using the local VMT divided by 640, which is very straightforward. The Distance Ratio is within $(0, 1]$, and higher value means the assumption made in the derivation about the average local distance traveled fits a certain local network better.

Based on the distribution of DR among 35 networks, the author divided them into three intervals: $(0, 0.5], (0.5, 0.7]$, and $(0.7, 1.0]$. If the DR is large, it means that the estimated travel distance is very close to actual travel distance, which can prove the accuracy of the proposed models in these certain patterns as well. However, if the DR is very small, it indicates that travelers actually have to go a much longer distance to leave the community than assumed. The specific classification results are shown in Table 4.32.

4.7.1 Density Ratio Model

The low DR interval includes 13 example networks (ID=$12 \rightarrow 14, 21, 22, 24 \rightarrow 28, 31 \rightarrow 35$), the medium DR interval includes 11 example networks (ID=$6 \rightarrow 9, 10, 11, 16, 20, 23, 26, 33$), and the high DR interval includes 11 example networks (ID=$1 \rightarrow 5, 15, 17 \rightarrow 19, 29, 30$).

Table 4.31: Distance Ratio of 35 Networks

ID	VMT_L	Actual Travel Distance	Estimated Travel Distance	Distance Ratio
1	1596.90	2.50	1.83	0.73
2	1468.07	2.29	1.73	0.76
3	1252.86	1.96	1.67	0.85
4	1044.92	1.63	1.58	0.97
5	1537.15	2.40	1.76	0.73
6	1705.91	2.67	1.85	0.69
7	1875.50	2.93	1.84	0.63
8	2006.39	3.13	1.83	0.58
9	1933.45	3.02	1.94	0.64
10	2256.31	3.53	1.96	0.56
11	2295.96	3.59	1.87	0.52
12	4740.84	7.41	2.03	0.27
13	14608.41	22.83	2.00	0.09
14	2613.75	4.08	1.87	0.46
15	1596.70	2.49	1.77	0.71
16	1908.87	2.98	1.70	0.57
17	1388.79	2.17	1.67	0.77
18	1199.35	1.87	1.64	0.88
19	1313.84	2.05	1.64	0.80
20	1832.15	2.86	1.66	0.58
21	2462.78	3.85	1.68	0.44
22	2778.49	4.34	1.69	0.39
23	1559.06	2.44	1.66	0.68
24	3100.33	4.84	1.70	0.35
25	3661.29	5.72	1.71	0.30
26	1876.07	2.93	1.67	0.57
27	2196.07	3.43	1.69	0.49
28	2756.47	4.31	1.70	0.40
29	1142.77	1.79	1.68	0.94
30	1350.51	2.11	1.75	0.83
31	3670.00	5.73	2.13	0.37
32	13530.00	21.14	1.99	0.09
33	2370.00	3.70	1.89	0.51
34	2753.00	4.30	2.11	0.49
35	2710.00	4.23	1.97	0.47

4.7.1.1 Local Road VMT vs. Collector Road VMT

Following the same procedure, the regression equations for the three different intervals are listed as follows.

Table 4.32: Network Classifications: DR

$DR \in (0, 0.5]$		$DR \in (0.5, 0.7]$		$DR \in (0.7, 1.0]$	
ID	DR	ID	DR	ID	DR
13	0.09	33	0.51	15	0.71
32	0.09	11	0.52	5	0.73
12	0.27	10	0.56	1	0.73
25	0.30	16	0.57	2	0.76
24	0.35	26	0.57	17	0.77
31	0.37	20	0.58	19	0.80
22	0.39	8	0.58	30	0.83
28	0.40	7	0.63	3	0.85
21	0.44	9	0.64	18	0.88
14	0.46	23	0.68	29	0.94
35	0.47	6	0.69	4	0.97
34	0.49				
27	0.49				

$$\frac{VMT_L}{VMT_C} = \begin{cases} -2.09\frac{\rho_3}{\rho_2} + 14.16\frac{\rho_3}{\rho_1} + 0.30, & DR \in (0, 0.5] \\ -0.01\frac{\rho_3}{\rho_2} + 3.25\frac{\rho_3}{\rho_1} + 0.07, & DR \in (0.5, 0.7] \\ 0.15\frac{\rho_3}{\rho_2} + 2.43\frac{\rho_3}{\rho_1} + 0.03. & DR \in (0.7, 1.0] \end{cases}$$

The R^2 for the regression model within the first interval is only 0.26, which shows that the proposed model is not accurate in estimating the local VMT of networks wherein the actual local distance traveled is far from the estimated value. This is easy to understand since the initial assumption is not right for such networks. Also, the R^2 for the second interval is 0.72 and 0.65 for the third interval.

So, the relative error needs to be calculated again to determine whether the regression model works well or not. The specific comparison results are shown in Table 4.33, Table 4.34, and Table 4.35.

The average relative error for the first interval is 56.46% and is not convincing. However, the average relative errors of the two other intervals are 8.33% and 10.36%,

Table 4.33: Local VMT Estimates for Low DR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
12	0.3851	0.4859	26.16%
13	1.0680	0.4640	56.55%
14	0.2038	0.3501	71.81%
21	0.1425	0.1352	5.15%
22	0.1608	0.1412	12.21%
24	0.1794	0.1474	17.85%
25	0.2119	0.1540	27.35%
27	0.1366	0.1785	30.69%
28	0.1714	0.1878	9.57%
31	0.2124	0.4317	103.27%
32	0.7823	0.4287	45.20%
34	0.1685	0.4610	173.56%
35	0.1663	0.4235	154.67%
		Average Error=	56.46%

Table 4.34: Local VMT Estimates for Medium DR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
6	0.1039	0.1184	12.27%
7	0.1149	0.1177	2.32%
8	0.1233	0.1173	5.06%
9	0.1199	0.1270	5.55%
10	0.1305	0.1291	1.08%
11	0.1764	0.1792	1.57%
16	0.1506	0.1264	19.09%
20	0.1419	0.1209	17.41%
23	0.0970	0.1276	24.01%
26	0.1167	0.1155	1.04%
33	0.1869	0.1829	2.21%
		Average Error=	8.33%

which are all quite small. So, the proposed model works well for networks where the actual local distance traveled is very close to the estimated value.

Table 4.35: Local Local VMT Estimates for High DR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
1	0.0995	0.1038	4.14%
2	0.0906	0.0886	2.27%
3	0.0761	0.0795	4.25%
4	0.0628	0.0690	9.01%
5	0.0930	0.0815	14.10%
15	0.1278	0.1278	0.06%
17	0.1081	0.0916	18.10%
19	0.1034	0.0883	17.03%
29	0.0686	0.0877	21.75%
30	0.0821	0.0943	12.95%
		Average Error=	10.36%

4.7.1.2 Collector Road VMT vs. Minor Arterial Road VMT

To obtain regression equations for estimating collector road VMT, use the following equations:

$$\frac{VMT_C}{VMT_{MA}} = \begin{cases} -0.23\frac{\rho_4}{\rho_3} + 1.33\frac{\rho_4}{\rho_2} + 0.10, & DR \in (0, 0.5] \\ -0.23\frac{\rho_4}{\rho_3} + 1.06\frac{\rho_4}{\rho_2} + 0.10, & DR \in (0.5, 0.7] \\ -0.10\frac{\rho_4}{\rho_3} + 1.00\frac{\rho_4}{\rho_2} + 0.08. & DR \in (0.7, 1.0] \end{cases}$$

The R^2 for the above three regression equations are 0.85, 0.96, and 0.87, respectively. The results show that the proposed regression model is very accurate in estimating the collector road VMT given the minor arterial road VMT.

4.7.2 Logarithmic Model

The low DR interval includes 13 example networks (ID=$12 \rightarrow 14, 21, 22, 24 \rightarrow 28, 31 \rightarrow 35$); the medium DR interval includes 11 example networks (ID=$6 \rightarrow 9, 10, 11, 16, 20, 23, 26, 33$), and the high DR interval includes 11 example networks (ID=$1 \rightarrow 5, 15, 17 \rightarrow 19, 29, 30$).

Table 4.36: Collector VMT Estimates for Low DR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
12	0.0912	0.1041	14.18%
13	0.1013	0.1041	2.76%
14	0.0950	0.1041	9.59%
21	0.1106	0.1044	5.58%
22	0.1106	0.1044	5.58%
24	0.1106	0.1044	5.58%
25	0.1106	0.1044	5.58%
27	0.0894	0.0917	2.59%
28	0.0894	0.0917	2.59%
31	0.0961	0.0917	4.54%
32	0.0665	0.0644	3.10%
34	0.1045	0.1044	0.13%
35	0.0626	0.0644	2.85%
		Average Error=	4.97%

Table 4.37: Collector VMT Estimates for Medium DR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
6	0.0631	0.0634	0.36%
7	0.0627	0.0634	1.00%
8	0.0626	0.0634	1.26%
9	0.0620	0.0634	2.22%
10	0.0665	0.0634	4.70%
11	0.0964	0.0977	1.32%
16	0.0817	0.0847	3.71%
20	0.0831	0.0847	1.85%
23	0.1029	0.0979	4.87%
26	0.0894	0.0849	4.99%
33	0.0939	0.0977	3.98%
		Average Error=	2.75%

4.7.2.1 Local Road VMT vs. Collector Road VMT

Then, the author uses the logarithmic method to develop the regression equations for the three intervals, which are shown as follows.

Table 4.38: Collector VMT Estimates for High DR Networks: Density Ratio Model

ID	Ratio	Model Result	Error (%)
1	0.0709	0.0723	2.00%
2	0.0716	0.0723	1.04%
3	0.0728	0.0723	0.56%
4	0.0735	0.0723	1.56%
5	0.0731	0.0723	0.96%
15	0.0925	0.0926	0.11%
17	0.0827	0.0870	5.21%
19	0.0819	0.0870	6.30%
29	0.0926	0.0872	5.74%
30	0.0914	0.0872	4.54%
		Average Error=	2.80%

$$ln(VMT_L) = \begin{cases} 1.30ln(VMT_C) + 1.19ln\rho_3 + 2.19ln\rho_2 - 0.55ln\rho_1 + 4.34, & DR \in (0, 0.5] \\ -0.74ln(VMT_C) - 0.36ln\rho_3 - 0.72ln\rho_2 - 0.72ln\rho_1 + 12.12, & DR \in (0.5, 0.7] \\ -0.60ln(VMT_C) + 0.02ln\rho_3 + 0.03ln\rho_2 - 0.49ln\rho_1 + 13.25. & DR \in (0.7, 1.0] \end{cases}$$

The R^2 of the regression equation for the first interval is only 0.16 with an average relative error of 36.20% (as shown in Table 4.39), so that this logarithmic regression model does not fit the networks very well where actual local distance traveled is far away from the estimated value. The R^2 for the other two intervals are 0.80 and 0.91. Specific results are shown in Table 4.40 and Table 4.41. The average relative errors of these two intervals are only 4.37% and 3.79%, respectively.

From the results shown in the above tables, the average relative errors are very small, so the logarithmic regression model best fits the networks where actual local distance traveled is very close to the estimated value.

Table 4.39: Local VMT Estimates for Low DR Networks: Logarithmic Model

ID	$ln(VMT_L)$	$ln(VMT_L)$(Model)	VMT_L	VMT_L(Model)	Error (%)
12	8.4640	8.5043	4740.84	4935.89	4.11%
13	9.5894	8.6215	14608.41	5549.92	62.01%
14	7.8685	8.4209	2613.75	4541.14	73.74%
21	7.8090	8.0356	2462.78	3089.07	25.43%
22	7.9297	8.0478	2778.49	3126.77	12.53%
24	8.0393	8.0602	3100.33	3165.81	2.11%
25	8.2056	8.0729	3661.29	3206.34	12.43%
27	7.6944	7.6045	2196.07	2007.16	8.60%
28	7.9217	7.6292	2756.47	2057.45	25.36%
31	8.2079	8.1430	3670.00	3439.10	6.29%
32	9.5127	8.8080	13530.00	6687.21	50.57%
34	7.9204	8.4001	2753.00	4447.34	61.55%
35	7.9047	8.7194	2710.00	6120.72	125.86%
				Average Error=	36.20%

Table 4.40: Local VMT Estimates for Medium DR Networks: Logarithmic Model

ID	$ln(VMT_L)$	$ln(VMT_L)$(Model)	VMT_L	VMT_L(Model)	Error (%)
6	7.4419	7.5303	1705.91	1863.72	9.25%
7	7.5366	7.5236	1875.50	1851.17	1.30%
8	7.6041	7.5203	2006.39	1845.08	8.04%
9	7.5671	7.6648	1933.45	2131.90	10.26%
10	7.7215	7.6396	2256.31	2078.82	7.87%
11	7.7389	7.7271	2295.96	2268.92	1.18%
16	7.5543	7.5723	1908.87	1943.65	1.82%
20	7.5132	7.4828	1832.15	1777.28	3.00%
23	7.3518	7.3868	1559.06	1614.48	3.55%
26	7.5369	7.5196	1876.07	1843.90	1.71%
33	7.7706	7.7700	2370.00	2368.51	0.06%
				Average Error=	4.37%

4.7.2.2 Collector Road VMT vs. Minor Arterial Road VMT

Following the same procedure, the regression equations estimating collector road VMT are listed below.

Table 4.41: Local VMT Estimates for High DR Networks: Logarithmic Model

ID	$ln(VMT_L)$	$ln(VMT_L)$(Model)	VMT_L	VMT_L(Model)	Error (%)
1	7.3758	7.4351	1596.90	1694.43	6.11%
2	7.2917	7.2893	1468.07	1464.58	0.24%
3	7.1332	7.1710	1252.86	1301.16	3.86%
4	6.9517	7.0011	1044.92	1097.82	5.06%
5	7.3377	7.1949	1537.15	1332.67	13.30%
15	7.3757	7.3786	1596.70	1601.41	0.29%
17	7.2362	7.2232	1388.79	1370.82	1.29%
19	7.1807	7.1859	1313.84	1320.66	0.52%
29	7.0412	7.0792	1142.77	1187.00	3.87%
30	7.2082	7.1737	1350.51	1304.64	3.40%
				Average Error=	3.79%

$$ln(VMT_C) = \begin{cases} ln(VMT_{MA}) - 0.73ln\rho_4 + 0.62ln\rho_3 - 0.71ln\rho_2 - 5.41, & DR \in (0, 0.5] \\ 3.84ln(VMT_{MA}) + 0.10ln\rho_4 + 1.88ln\rho_3 - 0.66ln\rho_2 - 25.36, & DR \in (0.5, 0.7] \\ ln(VMT_{MA}) - 0.43ln\rho_4 + 0.41ln\rho_3 - 0.67ln\rho_2 - 4.50. & DR \in (0.7, 1.0] \end{cases}$$

The R^2 for these three intervals are 0.92, 0.97, and 0.99, respectively. It shows that the logarithmic regression model works well for all 35 networks when estimating collector road VMT given minor arterial road VMT. The average relative errors of all three intervals are also given (shown in Table 4.42, Table 4.43, and Table 4.44).

4.8 Summary

In this chapter, the R^2 and relative error of the specific regression model under different classification measures are generated. Figure 4.13a, Figure 4.13b, Figure 4.13c, and Figure 4.13d show detailed comparisons between the different classification measures. Here the Distance Ratio is still categorized under the connectivity level just for the explanatory purpose and conveniences.

Table 4.42: Collector VMT Estimates for Low DR Networks: Logarithmic Model

ID	$ln(VMT_C)$	$ln(VMT_C)$(Model)	VMT_C	VMT_C(Model)	Error (%)
12	9.4182	9.4670	12310.20	12926.19	5.00%
13	9.5236	9.4670	13678.66	12926.19	5.50%
14	9.4592	9.4670	12825.87	12926.19	0.78%
21	9.7572	9.7460	17278.63	17085.86	1.12%
22	9.7572	9.7460	17278.63	17085.86	1.12%
24	9.7572	9.7460	17278.63	17085.86	1.12%
25	9.7572	9.7460	17278.63	17085.86	1.12%
27	9.6852	9.7093	16078.23	16469.45	2.43%
28	9.6852	9.7093	16078.23	16469.45	2.43%
31	9.7573	9.7093	17280.00	16469.45	4.69%
32	9.7582	9.7284	17294.65	16787.44	2.93%
34	9.7011	9.7460	16335.00	17085.86	4.60%
35	9.6986	9.7284	16294.65	16787.44	3.02%
				Average Error=	2.76%

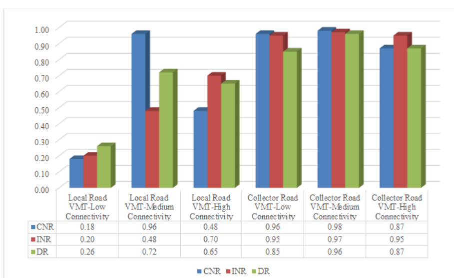
Table 4.43: Collector VMT Estimates for Medium DR Networks: Logarithmic Model

ID	$ln(VMT_C)$	$ln(VMT_C)$(Model)	VMT_C	VMT_C(Model)	Error (%)
6	9.706316	9.7100	16420.99	16481.03	0.37%
7	9.700013	9.7100	16317.83	16481.03	1.00%
8	9.697459	9.7100	16276.20	16481.03	1.26%
9	9.687953	9.7100	16122.20	16481.03	2.23%
10	9.758074	9.7100	17293.29	16481.03	4.70%
11	9.473716	9.4608	13013.15	12845.53	1.29%
16	9.44769	9.4567	12678.84	12793.96	0.91%
20	9.465762	9.4567	12910.06	12793.96	0.90%
23	9.685222	9.6852	16078.23	16078.27	0.00%
26	9.685222	9.6852	16078.23	16078.26	0.00%
33	9.447781	9.4608	12680.00	12845.53	1.31%
				Average Error=	1.27%

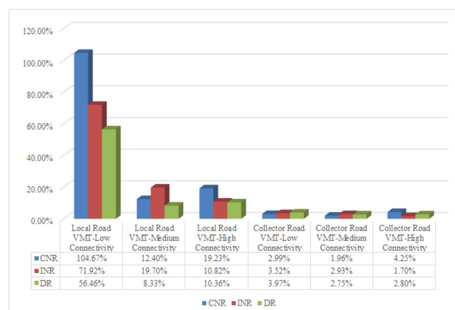
Based on the results from the regression analysis and the theoretical models (density ratio model and logarithmic model), all models performed well in estimating collector road VMT based on accurate minor arterial road VMT data. For estimat-

Table 4.44: Collector VMT Estimates for High DR Networks: Logarithmic Model

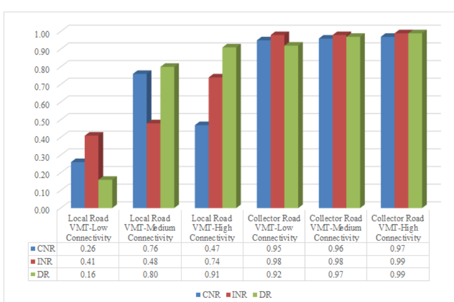
ID	$ln(VMT_C)$	$ln(VMT_C)$(Model)	VMT_C	VMT_C(Model)	Error (%)
1	9.6837	9.7037	16054.02	16378.04	2.02%
2	9.6932	9.7037	16206.90	16378.04	1.06%
3	9.7091	9.7037	16467.47	16378.04	0.54%
4	9.7192	9.7037	16634.29	16378.04	1.54%
5	9.7132	9.7037	16534.01	16378.04	0.94%
15	9.4327	9.4327	12490.54	12490.64	0.00%
17	9.4607	9.4555	12844.47	12778.37	0.51%
19	9.4503	9.4555	12712.41	12778.37	0.52%
29	9.7203	9.7140	16651.91	16547.65	0.63%
30	9.7077	9.7140	16443.75	16547.65	0.63%
				Average Error=	0.84%



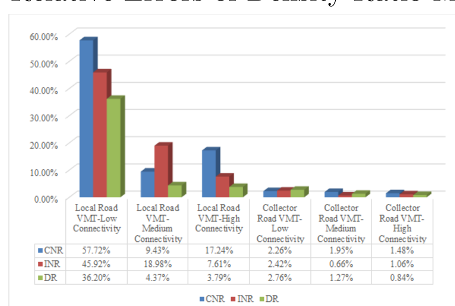
(a) R^2 of Density Ratio Model



(b) Relative Errors of Density Ratio Model



(c) R^2 of Logarithmic Model



(d) Relative Errors of Logarithmic Model

Figure 4.13: Comparison Graphs

ing local road VMT, the theoretical models are still robust for medium and high connectivity networks, but not for low connectivity networks. The reason is that the local VMT of low connectivity networks ($CNR \leq 0.5$) change dramatically related to the specific patterns. The conclusions are almost the same in the cases of Distance Ratio measurement and Link-Node Ratio measurement.

Overall, the logarithmic models perform better than the density ratio models in estimating both local and collector road VMT.

5. PRACTICAL APPLICATIONS OF THE METHOD

In this chapter, proposed models in this thesis will be tested under real situations to assess their applicability. Then a framework is proposed for the models including data needs and data use as well as a procedure of practical application.

5.1 Case Studies

5.1.1 Minneapolis-Hennepin County

In the first case, the author used the Hennepin County Urban VMT data [26] (2007-2013) obtained from the Minnesota Department of Transportation (MnDOT) to test the proposed models derived in the last chapter. Minneapolis is the largest city in the state of Minnesota, which is also the county seat of Hennepin County. Moreover, the roadway structure of Minneapolis is mainly in a grid network while most of the simulation local networks are also in grid networks. It is assumed that the overall roadway structure of Hennepin County can be represented by the roadway patterns of Minneapolis.

The basic method used by the Minnesota DOT to calculate VMT is multiplying average annual daily traffic (AADT) by the centerline mileages of each roadway segment under consideration. So the VMT data is the average vehicle miles per day for all vehicles. The Minnesota DOT obtained the AADT for unsampled roadway networks (minor collector or local roads) from three different sources:

- Former county road: If the minor collector or local road used to be a county road, it may have an AADT assigned to it, which came from an earlier time when it was part of the traffic count program.
- A default value derived from limited sampling over 25 years ago for use with

new roadways.

- Estimates or special counts based on one-time counts taken for various purposes.

This thesis's proposed regression models were tested based on actual VMT data to see how well they work. Figure 5.1 shows the map of Hennepin County (red area) captured from a Google Maps and Figure 5.2 is an example of roadway structures in Minneapolis. The figure shows that the roadway structure in Minneapolis is a very typical grid network.

After investigating all the three connectivity categories, the author found that the medium connectivity category models are most accurate in estimating local and collector road VMT. So, the author used the following equation to estimate local road VMT, which was derived and originally placed in Chapter 4 based on LNR.

$$\frac{VMT_L}{VMT_C} = 0.20\frac{\rho_3}{\rho_2} + 8.57\frac{\rho_3}{\rho_1} - 0.04. \tag{5.1}$$

The detailed comparison results are shown in Table 5.1. Columns 2 and 3 are the roadway density ratios, and column 4 is the actual local VMT data of Hennepin County.

Based on the results shown in the above table, the proposed model derived from simulation data works quite well in real situations with an average error of only 5.77%.

Next, the collector road VMT estimation model was tested. The specific format of the equation was derived based on the distance ratio (DR) in Chapter 4.

$$\frac{VMT_C}{VMT_{MA}} = -0.23\frac{\rho_4}{\rho_3} + 1.06\frac{\rho_4}{\rho_2} + 0.10. \tag{5.2}$$

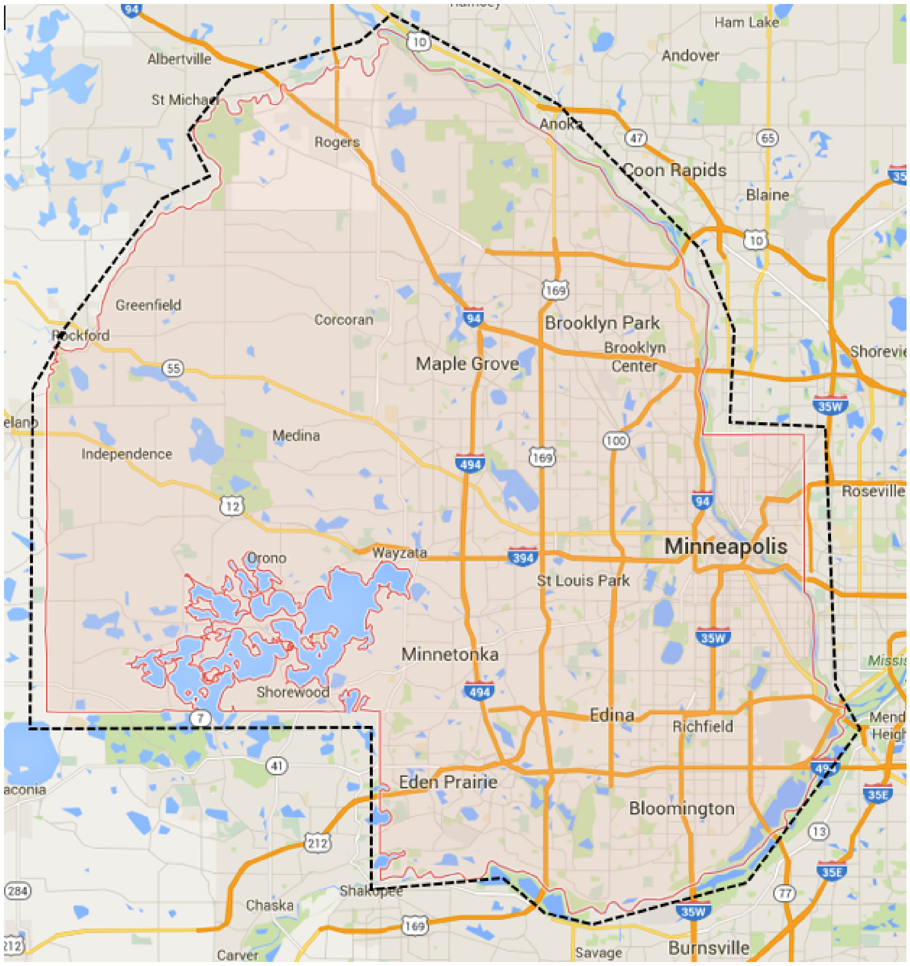


Figure 5.1: Map of Hennepin County. (*Source*: Google Maps, 2015 [27])

The comparison results of collector road VMT estimations were obtained which are shown in Table 5.2.

The average error is 43.40 %, which is not as good as local road VMT estimations. If calibrating and adjusting the parameters according to the real situation, there is a very high possibility that a much more accurate VMT estimation data can be obtained on lower functional classes of roadways.

For example, if changing the noise parameter from 0.10 to (-0.03) without modifying the parameters of the two variables, the average error will drop dramatically

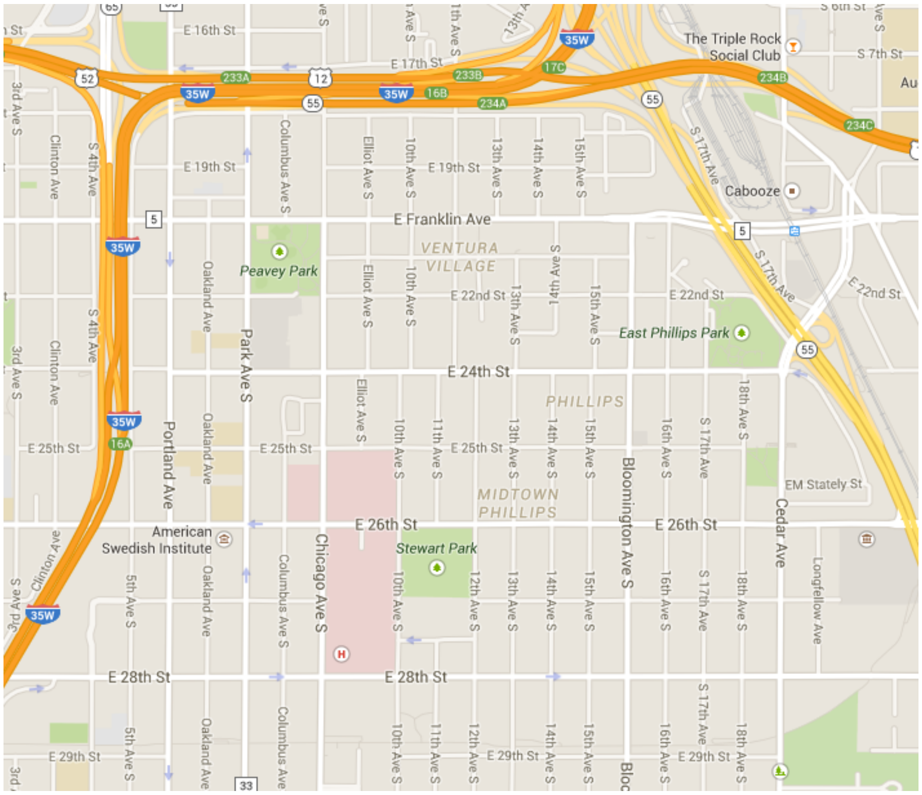


Figure 5.2: Example Layout of Roadway Structure in Minneapolis. (*Source*: Google Maps, 2015 [28])

to 8.94%. The detailed results are shown in Table 5.3.

Moreover, based on the results of Minneapolis, it is reasonable to suggest that the proposed models will work well for some major cities like Minneapolis, which also have very typical grid road network patterns. However, even though some big cities have grid road networks, the proposed models may not work well. For example, in New York, a very large percentage of traffic is transit traffic, so the traffic characteristics on that city's road network will be quite different from others even though the road network is in the grid format.

Table 5.1: Urban Local Road VMT Estimation of Hennepin County

Year	$\frac{\rho_3}{\rho_2}$	$\frac{\rho_3}{\rho_1}$	VMT_L	VMT_L(Model)	Error (%)
2007	1.0828	0.1583	3231129.00	3682058.17	13.96%
2008	1.1085	0.1618	3366306.00	3537267.67	5.08%
2009	1.1325	0.1641	3367607.00	3549535.86	5.40%
2010	1.1562	0.1642	3382411.00	3705784.97	9.56%
2011	1.2250	0.1635	3498908.00	3483609.52	0.44%
2012	1.2304	0.1627	3505371.00	3419444.26	2.45%
2013	1.2278	0.1607	3505886.00	3382526.20	3.52%
Average					5.77%

Table 5.2: Urban Collector Road VMT Estimation of Hennepin County

Year	$\frac{\rho_4}{\rho_3}$	$\frac{\rho_4}{\rho_2}$	VMT_C	VMT_C(Model)	Error (%)
2006	0.3793	0.4208	2386097.00	3071046.62	28.71%
2007	0.3850	0.4169	2401312.00	3074651.91	28.04%
2008	0.3742	0.4148	2255186.00	3192666.20	41.57%
2009	0.3723	0.4304	2318729.00	3232083.97	37.07%
2010	0.3723	0.4304	2318729.00	3178364.04	37.07%
2011	0.3786	0.4638	2169106.00	3391105.17	56.34%
2012	0.3767	0.4634	2136616.00	3368225.47	57.64%
2013	0.3781	0.4643	2136972.00	3435617.07	60.77%
Average					43.40%

5.1.2 Bryan/College Station-Brazos County

In the second case study, the VMT data of College Station and Bryan are used to test the proposed models. Both cities are located in Brazos County, TX. Figure 5.3 is a geographical map of the Brazos County (red area) captured from Google Maps.

The 2013 VMT data shown in Table 5.4 was obtained from the Bryan-College Station (BCS) metropolitan planning organization (MPO). Such VMT data is calculated based on the RoadHighway Inventory Network (RHiNo) dataset owned by TXDOT, which has the Average Daily Traffic (ADT) for the whole of Brazos County

Table 5.3: Urban Collector Road VMT Estimation (modified) of Hennepin County

Year	$\frac{\rho_4}{\rho_3}$	$\frac{\rho_4}{\rho_2}$	VMT_C	VMT_C(Model)	Error (%)
2006	0.3793	0.4208	2386097.00	2200952.85	7.76%
2007	0.3850	0.4169	2401312.00	2193059.64	8.67%
2008	0.3742	0.4148	2255186.00	2277751.16	1.00%
2009	0.3723	0.4304	2318729.00	2339297.79	0.79%
2010	0.3723	0.4304	2318729.00	2300416.71	0.79%
2011	0.3786	0.4638	2169106.00	2517359.44	16.06%
2012	0.3767	0.4634	2136616.00	2500497.57	17.03%
2013	0.3781	0.4643	2136972.00	2551491.75	19.40%
Average					8.94%

for 2013. The method to calculate VMT for different classes of roadways is multiplying ADT by each roadway segment and adding them together. But this dataset is not open to the public. The total mileage of each roadway classification is also included in the table as well as roadway length and VMT of the rest areas in Brazos County except for Bryan and College Station. All the VMT data in the table is the average VMT of each roadway classification per day.

After investigating all the three connectivity categories, medium connectivity category models proved to be most accurate in estimating local and collector road VMT in this case. For calculating urban local VMT estimates, the author used the following Equation 5.3, which is derived in Chapter 4 based on DR. Also, Equation 5.2 is used to calculate urban collector road VMT estimates. Here, the author also only considered the urban area, because the assumption of uniform traffic distribution may not hold anymore in rural areas.

$$\frac{VMT_L}{VMT_C} = -0.01\frac{\rho_3}{\rho_2} + 3.25\frac{\rho_3}{\rho_1} + 0.07. \tag{5.3}$$

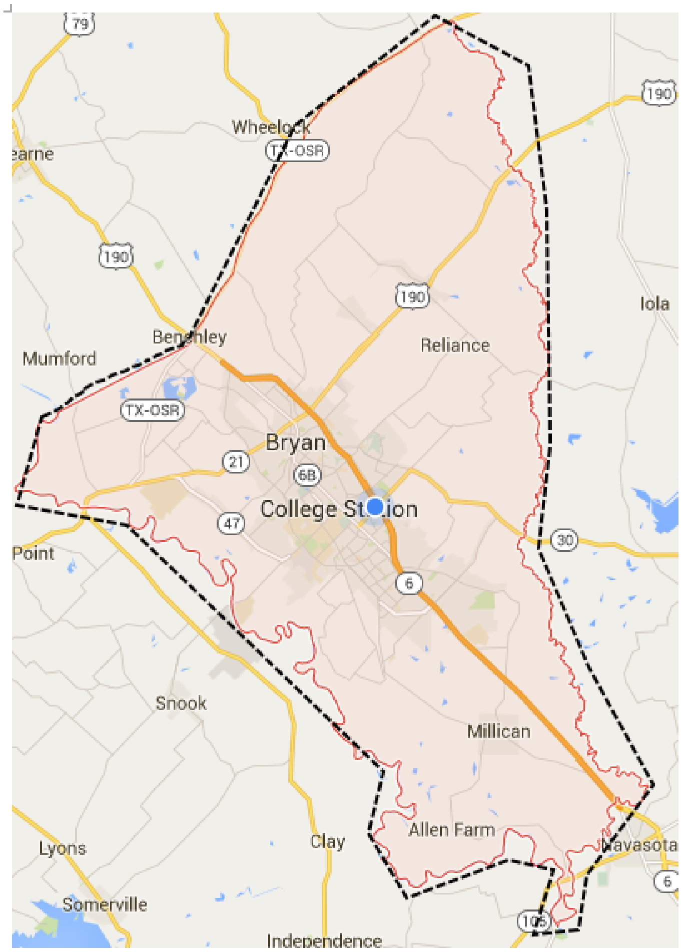


Figure 5.3: Map of Brazos County. (*Source*: Google Maps, 2015 [29])

The detail comparison results are shown in Table 5.5. Based on the estimation results shown in the table, it is very conspicuous that the average errors are much larger compared with Minnesota's recorded error rates. The reason is that the road network patterns in the BCS area are not in grid network, so the proposed equations are not robust in this case. However, this does not necessarily indicate that the proposed models are inapplicable for non-grid road networks, since the author only tested very limited data without recalibrating parameters. Figure 5.4 shows some typical road network patterns in the BCS area. The local road networks in the BCS

Table 5.4: Total Length and Average Daily VMT of Different Roadway Classifications

	College Station		Bryan		Brazos County	
	Mileage	VMT	Mileage	VMT	Mileage	VMT
Rural Local	0.71	211.33	1.71	158.37	311.64	41177.45
Rural Major Collector	2.70	24851.89	0.40	586.92	98.98	158428.99
Rural Minor Arterial	4.51	16916.51	0.02	9.42	22.90	130233.19
Rural Minor Collector					94.89	64033.78
Rural Principal Arterial	1.33	34283.05	0.01	235.39	36.46	550519.79
Urban Collector	54.01	338799.66	65.59	196072.19	5.73	13471.42
Urban Local	126.50	45778.52	154.08	49200.13	26.09	5494.95
Urban Minor Arterial	27.58	207388.15	29.32	202045.34	8.27	15726.23
Urban Principal Arterial (OF&E)	10.15	373195.83	11.19	334811.62	1.68	34787.24
Urban Principal Arterial (Other)	30.69	717398.13	45.55	620404.44	6.28	107021.21

area are quite different from each other but identical patterns could not be shown based on these examples.

Table 5.5: Urban Local and Collector Road VMT Estimations of Different Area

	VMT_L	VMT_L(Model)	Error (%)	VMT_C	VMT_C(Model)	Error (%)
College Station: Urban	45778.52	262057.31	472.45%	338799.66	116339.74	65.66%
Bryan: Urban	49200.13	134093.62	172.55%	196072.19	115526.55	41.08%
Brazos County: Urban	5494.946	14623.43	166.13%	13471.42	21237.56	57.65%
Average			270.37%			54.80%

5.2 Practical Application Procedure

The basic assumption in the analysis is that trips are distributed uniformly in the local neighborhood. This procedure is mainly intended for estimating the VMT on lower functional classes of urban roadways at the city level. For cities with similar grid road network patterns as used in this analysis, such as Minneapolis, the equations derived can be applied directly. However, for other cities with irregular road network patterns or unevenly distributed demand, all the parameters in the proposed equations had to be recalibrated. Following is the application procedure for cities with grid road network patterns, which were used to obtain local VMT estimates. Four steps were used to establish the equations derived in this thesis which are listed as follows.

1. Collect characteristic information about local communities, such as number of links and nodes, to determine average connectivity level (e.g., low, medium, or high) for all the local communities in this city (the specific classification criteria are mentioned in Chapter 4). The boundaries of the local community were determined by city administration, a DOT or Metropolitan Planning

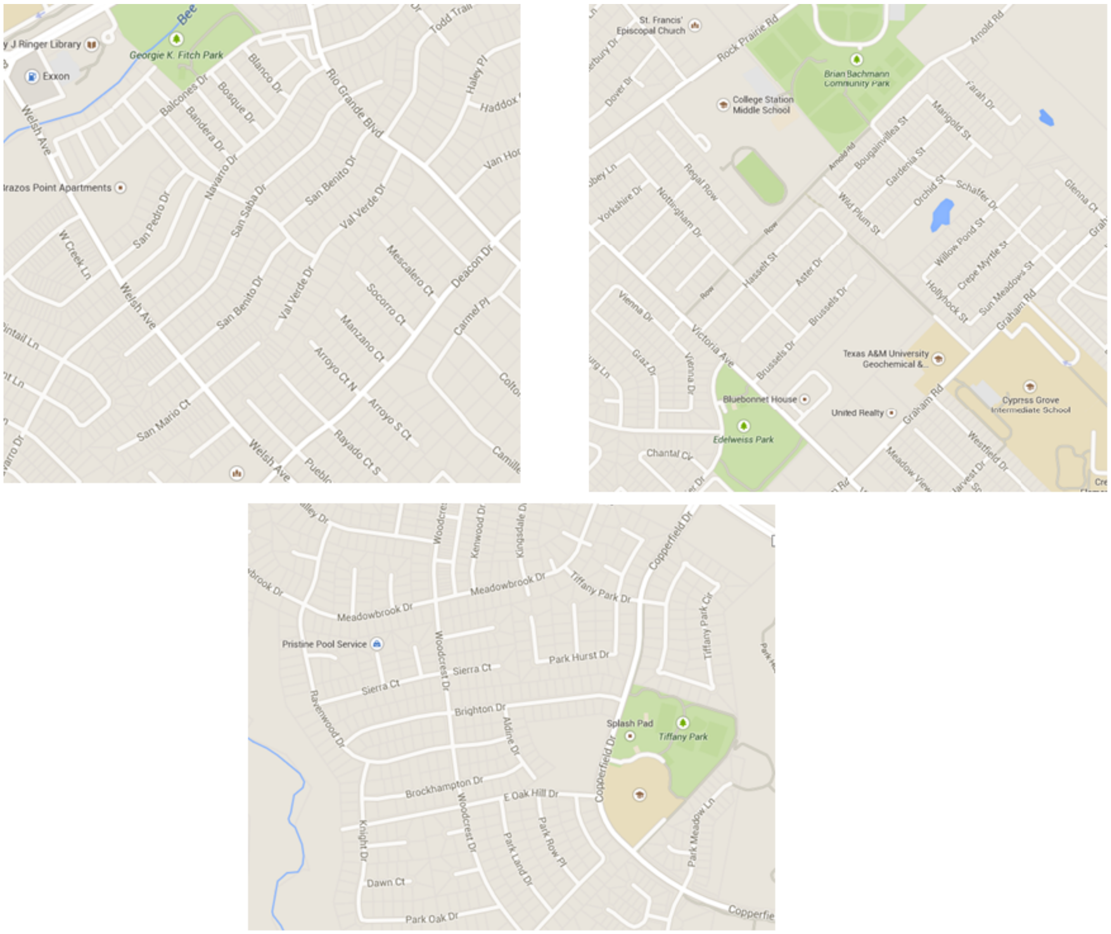


Figure 5.4: Local Road Network Pattern Examples in BCS Area. (*Source*: Google Maps, 2015 [30])

Organization (MPO) based on actual situations.

2. For cities with grid road network patterns, test the three proposed equations (density ratio or logarithmic equation) obtained by using different connectivity measures from the connectivity category determined in step 1. The specific formats of the proposed models that need to be tested can be found in Chapter 4. It is assumed that enough local and collector road VMT data are available to calibrate the regression equation, as well as the total length of each roadway

classification.

3. Choose the regression equation with the smallest relative error from step 2 and recalibrate the noise parameter by trial and error to obtain a regression equation that can generate the most accurate local VMT estimates. The noise parameter is used as a changeable variable to make the proposed regression equation fit various real situations.

4. Apply the calibrated regression equation to estimate the **future** (such an equation can be used for next several years) local VMT by using explanatory variables of higher classification road VMT and corresponding density data.

For cities with irregular (non-grid) road network patterns, the author cannot suggest any uniform procedure to estimate local VMT. This is because that unlike grid road networks, there are too many different patterns for non-grid road networks, and each pattern may need a specific model to estimate its VMT. So, the road network of a certain city needs to be investigated to derive specific regression models that can estimate its VMT accurately. The proposed regression equations from this study did not work well for irregular road network patterns as mentioned before.

Estimating collector road VMT by using a higher class road VMT can be conducted by following a similar procedure for grid network cities.

6. CONCLUSION AND FURTHER DISCUSSION

This study proposed a new perspective and new models to estimate the VMT on lower functional classes of roadways in grid networks by using higher class roadway VMT, and by using roadway density characteristics. By using idealistic shapes of communities, the author demonstrated that the VMT ratio between different classes of roadways has an inherent correlation with roadway densities, which allows us to use the actual VMT data for higher classes of roadways and use the roadway densities of relevant functional classes to estimate the total VMT on lower classes of roadways in grid networks. However, for non-grid networks, this method has not proven to be reasonable so far, and needs further investigation.

Subsequently, the author presented two types of regression models, one using density ratios as explanatory variables and the other using logarithmic values of roadway densities. In the former case, the ratio of VMT was the dependent variable while in the latter case, it was the VMT ratio of logarithmic value. The author set up several simulation networks to verify the proposed models using community road patterns categorized according to three different measures. The author also found that the proposed models worked well for medium and high connectivity networks, and worked poorly for low connectivity networks. Comparatively, the equation using logarithmic terms provided a better result in every numerical test.

The author also verified proposed regression equations by real examples, and applied the proposed regression equations directly in both cases. However, the two cases used different equations (Equation 5.1 for the Minneapolis case and Equation 5.3 for the Bryan/College Station case). The results show that the proposed regression models worked very well in estimating urban local VMT of grid networks (e.g., Minneapolis) with a relative error of about 6%. However, the relative error was much bigger in estimating local VMT of non-grid networks (e.g., Bryan/College Station) with a relative error of more than 50%. The VMT and roadway length information were provided by Minneapolis DOT and Bryan/College Station MPO.

Furthermore, the findings suggested a promising procedure to city or state (with grid road networks) DOTs for VMT estimation on lower functional classes of roadways. Roadway densities as well as VMT for higher functional classes of roadways are available and in general more accurate. Once the city or state DOT has calibrated specific regression models, it is reasonable to suggest that such models will work over a long time period without any significant further data collection requirement. The reason is that the derived inherent relationship of the VMT ratio between different classes of roadways will remain the same in the future. However, practical tests are still necessary to help prove the proposed procedure.

In this study, several assumptions were made to help simplify the derivation process. For example, the author assumed that households are uniformly distributed in a local neighborhood and roadways are in grid networks. Additionally, during the derivation process, the author often used the approximation method, especially when calculating the average distance traveled on each roadway class. All of these factors can be sources of errors or noises. There are three major categories for sources of errors.

- Network characteristics can include uneven distribution of local roadways with a local neighborhood and uneven distribution of collector roads and minor/principal arterial roads. For example, some local communities are not surrounded by closed collector roads nor are they surrounded by roads in the shape of a square or circle. Some collector roads are not surrounded by minor arterial roads in squares.

In this study, the proposed regression models were developed based on mainly grid networks, and the author used those proposed regression equations derived from simulation data directly in both of the two cases. The results turned out to be much better in estimating local VMT in the Minneapolis case (grid network with 10.13% error) than in the Bryan/College Station case (non-grid network with 270% error).

- Households characteristics can include asymmetric or uneven distribution of households or trip generating points in a local neighborhood and asymmetric distribution of final destinations of trips (in terms of the four general directions: NSEW). Travelers may not always attempt to get to higher class roads as quickly as assumed. For example, some travelers have their own travel habits, so they will choose their most familiar routes to get to their destinations, which may not be the shortest paths.

  In practice, uniform distribution assumption of both trip generating points and destinations is not reasonable in some cases. For example, in rural area, the trip generations will be sparsely scattered within a large area. In the case study of the Bryan/College Station metropolitan area, which falls under the category of small cities, travel destinations (working places) are concentrated in several nonuniform (off the grid) areas. The results of the Bryan/College Station case study showed that this possible source of errors can be quite significant.

- Approximation Errors are a possible source of errors occurs, which occur when using the approximation method to define the format of regression equations. This is because, in reality, the spacing of higher class roadways is not long enough compared with that of lower class roadways.

Simulation results show that the proposed models work well for medium and high connectivity networks, but work poorly for low connectivity networks. This indicates that the approximation error could be significant when applying the proposed format of regression models to low connectivity networks.

Last but not least, such low connectivity networks mainly exist in rural area and small cities.

- OD characteristics. These models assume that travelers traverse local, collector and arterial roads, ignoring trips within local communities or local trips between local communities that are on local roads.

In the proposed practical procedure, the proposed estimation models were intended to apply at the city level using accurate sampled or simulation local/collector VMT data as well as using roadway density data. So, from the macroscopic view, the first two possible sources of errors mentioned above had very little effect on the final results. For the third source of errors, the case study of Minneapolis has already verified that the set up of the proposed regression equations are quite accurate, since the final relative error is quite small considering the total VMT for a large city. The violations of these assumptions are reflected by calibrated coefficients in each regression model as well. Moreover, the practical implementation of the proposed models to estimating the local/collector VMT in Minneapolis proved that the method and regression models are promising in estimating VMT for lower functional classes of roadways in grid networks. However, even though they show promise, future work is still needed to see if they are robust or not.

Future work is still necessary to test more scenarios (rural area and small cities), including non-uniformly distributed demand in local networks. VMT in rural area is often needed. Moreover, it is still necessary to investigate if results (models) will change when the roadway network is not in grid format. As a special case, the author analytically showed that a circular type of network also gives rise to similar analytical equations. However, other common irregular networks still need to be investigated. Finally, more real cases need to be tested in order to check the practical application of the proposed models in various situations. Finally, the author hopes to find the appropriate model format or set up for different kinds of roadway networks accordingly.

To summarize, even though there are several sources of errors due to deviations from the assumptions the author made during the analytical deviation, this new method is reasonable and practical since most of the assumptions represent very common situations. The regression equations proposed include explanatory variables verified through analytical deviation, and the equations allow a calibration process of coefficients to account for those errors. Ultimately, the author hopes the findings will reveal a new direction for VMT estimation on local roads.

REFERENCES

[1] Costa, Ashley. Vehicle Miles Traveled (VMT) Fee Financing Alternatives: Lessons Learned and Future Opportunities. PhD diss., University of Massachusetts Amherst, 2012.

[2] American Association of State Highway and Transportation Officials. *Federal Motor Fuel Taxes* . ASSHTO, Washington., DC. http://www.transportation-finance.org/funding_financing/funding/federal_funding/motor_fuel_taxes.aspx. Accessed August, 2015.

[3] Office of Highway Policy Information. *Highway Performance Monitoring System Field Manual*. OMB Control No. 2125-0028. FHWA, U.S. Department of Transportation, 2014.

[4] Federal Highway Administration. *State Practices Used to Report Local Area Travel*. FHWA, U.S. Department of Transportation, 2003.

[5] Federal Highway Administration. *Highway Functional Classification Concepts, Criteria and Procedures*. Publication FHWA-PL-13-026. FHWA, U.S. Department of Transportation, 2013.

[6] Hausman, Joseph., and Clarke, Justin. FHWA Functional Classification Guidance Update. Presented at Highway Information Seminar, Arlington, VA, 2012.

[7] Federal Highway Administration. *FHWA Functional Classification Guidelines*. FHWA, U.S. Department of Transportation, 2000.

[8] Federal Highway Administration. *Roadway Departure Safety: A Manual for Local Rural Road Owners*. Publication FHWA-SA-11-09. FHWA, U.S. Department of Transportation, 2011.

[9] Kumapley, Robert K., and Jon D. Fricker. Review of Methods for Estimating Vehicle Miles Traveled. *Transportation Research Record: Journal of the Transportation Research Board*, Issue. 1551, 1996, p. 59-66.

[10] Rentziou, Aikaterini, Konstantina Gkritza, and Reginald R. Souleyrette. VMT, Energy Consumption, and GHG Emissions Forecasting for Passenger Transportation. *Transportation Research Part A: Policy and Practice*, Vol. 46, Issue 3, 2012, p.487-500.

[11] Texas Commission on Environmental Quality Program. *TxLED VMT Estimation Project*. Cambridge Systematics, Inc., Cambridge, MA. `http://www.tceq.texas.gov/assets/public/implementation/air/am/contracts/reports/mob/TxLED_VMT_Estimation-csi.pdf`. Accessed Feb, 2015.

[12] Frawley, William E. *Local Street Vehicle Miles Traveled (VMT) Random Count Site Selection For Counties That Have Air Quality Conformity Issues.* Publication TTI-2002-18. Texas Transportation Institute, College Station, TX, 2002.

[13] Stone, Brian., Obermann, William., and Snyder, Stephanie. *A New Method for Estimating and Projecting Vehicle Miles of Travel Linkages to Landscape Change and Ozone Impacts to Northern Forests.* Publication Gen. Tech. Rep. NC-253. U.S. Department of Agriculture, Forest Service, North Central Research Station, 2005.

[14] Federal Highway Administration Nation Household Travel Survey. *Developing a Best Estimate of Annual Vehicle Mileage for 2009 NHTS Vehicles*. Oak Ridge National Laboratory, Oak Ridge, TN. `http://nhts.ornl.gov/2009/pub/BESTMILE.pdf`. Accessed Feb, 2015.

[15] Zhong, Ming, and Brody L. Hanson. GIS-based Travel Demand Modeling for Estimating Traffic on Low-class Roads. *Transportation planning and technology*, Vol. 32, No. 5, 2009, p. 423-439.

[16] Seaver, William L., Arun Chatterjee, and Mark L. Seaver. Estimation of Traffic Volume on Rural Local Roads. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1719, 2000, p. 121-128.

[17] Zhao, Fang, and Soon Chung. Estimation of Annual Average Daily Traffic in a Florida County Using GIS and Regression. *Transportation Research Record*, Vol. 1769, 2001, p. 113-122.

[18] Blume, Kelly, Marais Lombard, Shaun Quayle, Phill Worth, and John Zegeer. Cost-effective Reporting of Travel on Local Roads. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1917, 2005, p. 1-10.

[19] Wang, Sheng-Guo, Libin Bai, Xun Bao, Yue Liu, and Guangyi Cao. Novel Estimation Method of Community AADT and VMT Via Circuit Network Models and Simulation. Presented at Decision and Control and European Control Conference (CDC-ECC), 2011 50th IEEE Conference, Orlando, 2011.

[20] Qian, Jiayu. Estimating Vehicle Miles Traveled on Local Roads. Master Thesis., Texas A&M University, 2013.

[21] Barrett, Monica L., R. Clark Graves, David L. Allen, Jerry G. Pigman, Ghassan Abu-Lebdeh, Lisa Aultman-Hall, and Sarah T. Bowling. *Analysis of Traffic Growth Rates.* Kentucky Transportation Center, University of Kentucky, Kentucky. `http://uknowledge.uky.edu/cgi/viewcontent.cgi?article=1289&context=ktc_researchreports`. Accessed Mar, 2015.

[22] Southworth, Michael, and Eran Ben-Joseph. *Streets and the Shaping of Towns and Cities*. Island Press, Washington, D.C., 2003.

[23] Litman, T. *Roadway Connectivity Creating More Connected Roadway and Pathway Networks.* Victoria Transport Policy Institute. http://www.vtpi.org/tdm/tdm116.htm. Accessed Mar, 2015.

[24] Tresidder, Mike. *Using GIS to Measure Connectivity: An Exploration of Issues*. School of Urban Studies and Planning, Portland State University, Portland. http://web.pdx.edu/~jdill/Tresidder_Using_GIS_to_Measure_Connectivity.pdf. Accessed Apr, 2015.

[25] Dill, Jennifer. Measuring Network Connectivity for Bicycling and Walking. In TRB 2004 Annual Meeting CD-ROM. Presented at 83rd Annual Meeting of the Transportation Research Board, Washington, D.C., 2004.

[26] Transportation Data and Analysis Program. *VMT by Functional Class for each County*. Minnesota Department of Transportation, St. Paul, MN. http://www.dot.state.mn.us/roadway/data/data-products.html#VMT. Accessed Feb, 2015.

[27] Google Maps. (2015). *Hennepin County*. Retrieved from https://www.google.com/maps/place/Hennepin+County,+MN/@45.0155979,-93.752682,10z/data=!3m1!4b1!4m2!3m1!1s0x87f61d9215d9eea5:0xcc01715fd877449e.

[28] Google Maps. (2015). *Minneapolis Roadway Structure*. Retrieved from https://www.google.com/maps/place/USDA+Rural+Development/@44.9591832,-93.2629812,15.5z/data=!4m2!3m1!1s0x52b4a157d1e26e4f:0xebe25b405f16996e.

[29] Google Maps. (2015). *Brazos County*. Retrieved from https://www.google.com/maps/place/Brazos+County,+TX/data=!4m2!3m1!1s0x86468f8faf031331:0x60586710d5f11c6b?sa=X&ved=0CHQQ8gEwCmoVChMIvraQuuaDyQIVV-RjCh32-AdG.

[30] Google Maps. (2015). *Bryan/College Station Roadway Structure*. Retrieved from https://www.google.com/maps/@30.5978052,-96.3266634,16.75z.