Modeling and Algorithms of VMT and AADT Estimation for Community Area Traffic Networks

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Abstract: This paper presents new modeling methods and their algorithms for the VMT (Vehicle Miles Traveled) and AADT (Annual Average Daily Traffic) estimation of community traffic networks which are lack of monitoring systems. It is found that the total traffic amount at the entrances of a community has strong relationship with its household number. Three models are proposed to estimate and predict AADT and VMT in the community based on its household number, the road network topology, and drivers' common behavior in statistical sense. The automatic algorithm and software are developed for the new models. The models and methods are verified by the field sample measurement data.

Keywords: modeling, transportation, VMT, estimation, prediction.

1. INTRODUCTION

The VMT is very important and used in USA Federal Highway Administration (FHWA) funding formulas, decision making, planning, analysis, etc., including accident analysis, design and operation analysis of highway facilities, energy consumption, vehicle emissions estimate, air quality analysis, traffic impact assessing, budget estimate, and revenue allocation (Kumapley & Fricker 1996; FHWA 2010; Wang *et al*. 2010). It is required by the FHWA as part of the Highway Performance Monitoring System (HPMS) requirement (Kumapley & Fricker 1996; FHWA 2010). The VMT refers to total miles travelled by all vehicles on a road network, and is one of the most important measures to evaluate the utilization of highway systems by vehicles. Thus, the accurate VMT is needed for states and the FHWA to help these analyses, operations, designs, decisions, etc.

The estimation methods of the VMT can be classified into two categories: traffic-count-based and non-traffic-count-based (Fricker and Kumapley 2002; FHWA 2010). In traffic-count-based methods the actual counts of traffic volume are used to estimate the AADT and then the VMT. Based on the AADT and the length of each road section, the VMT can be calculated by accumulation of their multiplications. Unlike the traffic-count-based methods, the non-traffic-count-based VMT estimation methods use non-traffic data, usually socioeconomic data (e.g., fuel sales, populations, etc.) to estimate VMT (Liu and Kaiser 2006). Some related research work includes: Lingras, Sharma and Kalyar (2000) on traffic volume time series by the road type, Wolf, Oliveira and Thompson (2003) on the VMT and travel time by the statewide survey GPS study, Boile and Golias (2006) and Castro-Neto *et al*. (2009) on regression to the VMT estimation, and Xia *et al*. (2007) on the AADT estimation in FL. Recently, Yang, Wang and Bao (2011) proposed a local AADT estimation with effective smoothly clipped absolute deviation penalty (SCAD) procedure to select significant variable based on regression models. The traffic-count-based methods are the most common approach used to forecast VMT growth. e.g., the HPMS procedures are based on traffic count data. As commented in the literature, count-based methods are generally simple and easy to be implemented. However, they may be biased because the HPMS is particularly designed for statewide estimation of travel (high level functional roads), and as usual, they are not statistically valid on the roads with the functional class below the statewide level (Kumapley and Fricker 1996; FHWA 2010).

The statewide VMT has two parts: one is from monitored high level functional roads, and another is from un-monitored low level functional roads. The VMT of monitored roads can be easily obtained based on the monitoring system data to generate the AADT and then calculate the corresponding VMT. Thus, if we have an accurate estimate of AADT for un-monitored low level functional roads, especially for RMC (Rural Minor Collector) and local roads (we will refer it as local roads for simplicity below), then we can combine it with the monitored roads VMT to generate an accurate statewide VMT estimate.

However, how to estimate the AADT and VMT in local roads is a national recognized long-time existing difficult problem because of no monitoring systems on these roads (Kumapley and Fricker 1996; Tweedie 2000; FHWA 2009). Recently, some most noteworthy state activities for the local road VMT were reported in FHWA (2009) as follows.

(a) Georgia State divided roadways into 16 groups by four population groups and four road surface groups, and generated the group AADT and VMT by sampling average.

(b) Kentucky State introduced a factor curve to fit the AADT relationship between the minor collector and the local roads by counties.

(c) New York State developed a group method for sampling according to the local road classification and the area type.

These new activities make progress, improve the estimation and reduce the required sample numbers. It is noticed that more than 20 states apply a method that uses a limited sample or its combination of short-term counts to estimate average AADT for local roads (FHWA 2010; Sabry et al. 2007). However, the challenging problems are how to group and how to sample these local roads because of no available information before the sampling measurements.

Moreover, the majority road mileages are from local roads. For example, NCDOT (2008, 2010) pointed out that 72% of the statewide road mileages are local roads. They make a certain part of total VMT, even though their AADT may be not so high. It is also noticed that a certain percentage of local roads are residential community roads, especially as a major part in urban areas. Thus, it is important to develop new methods to solve these problems and provide good estimation of the AADT and VMT for the local roads.

In this paper, we present a modeling approach with three new models for the AADT and VMT estimation on the local road networks in communities without the measurements or with few samplings. The first model is the shortest path model which offers the lower bound of the VMT. The second model introduces a turn penalty in view of the driving behaviors, and the third model is the probability model. We also describe our data collection design for the model development and validation. It is interesting to find from the data that the total entrance AADT of each observed community is linearly related its household number. The corresponding algorithms are developed based on the GIS road networks, which can automatically estimate the AADT and VMT on the community road networks. The experiments data show that the proposed models can well predict the average AADT and VMT in the sense of statistics, which are better than common sampling methods in the example.

The paper is organized as follow. Section 2 addresses the data collection design. Section 3 presents our new approach for modeling. Then three models are presented in Sections 4 to 6, respectively. Section 7 provides experiment results, model validation and a comparison with the common methods. Finally, Section 8 concludes this paper.

2. DATA COLLECTION AND ANALYSIS

In order to study the AADT and VMT of communities on local roads, we first designed our sampling and data collection plan to measure the traffic in the community areas in the Mecklenburg County for modeling as follows.

(1) We divided the Mecklenburg county into 400 (20×20) small areas. Then we randomly selected areas in a sequence from these 400 small areas via a computer random number generation for field selection and test.

(2) In the randomly selected areas, based on their features we further selected the roads which are usually not monitored by the traffic survey group (TSG) for counting. Also, we measured the entrance traffic counts to/exit communities to know the total traffic into and out communities for modeling.

(3) The measurement schedule was as a 2-days or 7-days continuous count by 4 ADR-1000 and 16 TT-6 instruments in two groups from February 2009 to November 2009.

(4) The data were converted to the AADT by the season factors (based on month, week and day) and the axle factors.

In order to analyze the relationship between the household number and the total entrance AADT, we take the regression analysis on the measurement data in statistics. Based on the measurements of 16 communities in Mecklenburg County, we obtain a regression curve as shown in Fig. 1. Each dot represents a community. The x-axis is the household number of each community, and the y-axis is the total entrance AADT of each community. From the data, we find a linear relationship between them in Mecklenburg as

$$TotalEntranceAADT = 10.343 \times Household \qquad (1)$$

This linear regression has the p-value less than 0.0001 and $R^2 = 0.9951$. This R^2 value is very close to 1, i.e., a simple linear model (1) is sufficient to fit the relationship for communities in the region. It means that the total entrance AADT of a community can be estimated by the number of households, which is easily obtained from the database. It may also be reasonable to think that different cities may have their respective linear models by sample tests.
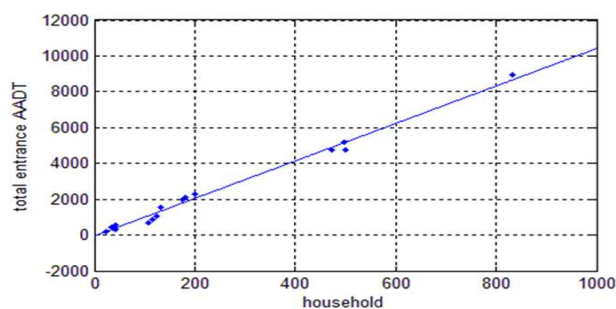

Fig.1. Community household numbers and their total entrance AADTs

3. COMMUNITY TRAFFIC MODELING

In this section, we present a new modeling approach for the estimation and prediction of the AADT and VMT on community road networks. This approach needs only the community entrance traffic amounts, which may be obtained either by limited measurements at the entrances or by the total household numbers without the traffic monitoring.

The road networks can be regarded as a graph $G = (N, E)$, which consists of a nonempty node set $N = \{n_1, n_2, …, n_m\}$, and an edge set $E = \{e_1, e_2, …, e_k\}$, that is a set of unordered pairs of distinct elements of N (Rosen 1999). For each edge e_i in E, it has two attributes: its household number $hh(e_i)$, and its edge length $l(e_i)$. The total household number of a community can be calculated as

$$TotalHH = \sum_{i=1}^{k} hh(e_i) \qquad (2)$$

The total entrance AADT of a community is $TEAADT$ as

$$TEAADT = \sum_{n_i \in V} AADT(n_i) \qquad (3)$$

where $AADT(n_i)$ is the AADT at entrance n_i, and V is the set of entrance nodes.

The modeling approach is based on our following formulas:

$$AADT_R = \int_{s \in S_o} \sum_{i=1}^{v} h(s)\, p_i(s) p_{iR}(s) ds \qquad (4)$$

$$VMT = \oint_{s \in S_o} \sum_{i=1}^{v} h(s) p_i(s) d_i(s) ds \qquad (5)$$

where $AADT_R$ is the AADT on a road R, v is the total numbers of community entrances, variable s is a point on this community road network S_o, $h(s)$ is the AADT contribution of a household located at s, $p_i(s)$ is the probability of $h(s)$ going to entrance i, $p_{iR}(s)$ is the conditional probability of $h(s)$ going through road R to entrance i, $d_i(s)$ is the route distance from s to entrance i that $h(s)$ takes, and the integration is for variable s along all roads in this network S_o. Equations (4) and (5) are the core for our modeling. From (4) and (5), we further derive algebraic formulas based on some simplifications, e.g., even distributions, for programming. Along this approach, we develop the following three models.

4. SHORTEST PATH MODEL

The first model is the shortest path model which offers the lower bound of the VMT estimations. The model is established with two assumptions: (i) each household runs the shortest path to its nearest community entrance, and (ii) the households of a road are evenly distributed along it.

We further evenly distribute the total entrance AADT to each household as its contribution $h(s)$ in (4) and (5) as a constant S, called "supply rate" here. Thus, it is

$$S = TEAADT / TotalHH \qquad (6)$$

In calculating the lower bound, the traffic from or to the household is via its nearest entrance, say q, and its distance $d_{i=q}(s)$ to the entrance q is the shortest distance, and the probability $p_i(s)$ of $h(s)$ to entrance i is 1 as $i = q$, or 0 as $i \neq q$. The shortest path between two points on the graph $G = (V, E)$ can be calculated by Dijkstra's algorithm (Dijkstra 1959). We can divide the community graph into divisions according to its nearest entrance. Fig. 2 shows a community which has three entrances and is marked as three divisions by different colors. There are four roads with two different colors because each of them has two different nearest entrances, i.e., one part of this road is near to one entrance, and the rest part of it is near to another entrance.
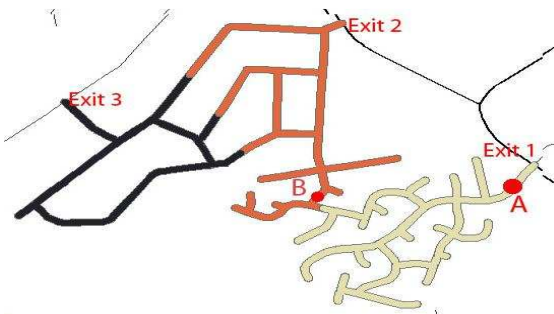

Fig. 2. Divisions according to their nearest entrances

Thus, we may have two different cases in estimating a road AADT: (i) two nodes of a road (edge) have the same nearest entrance, and (ii) they have different nearest entrances. In case (i), two nodes usually have the same and common

shortest path to the same nearest entrance except that one node has an additional piece of the road itself. For example as shown in Fig. 3, edge e_6 has its shortest path (e_2, e_1) via nodes (n_{11}, n_2) to its nearest entrance n_1. A rare situation in case (i) is that two nodes have a same nearest entrance, but two different shortest paths to this entrance. For this rare situation, we may treat it similarly as described to case (ii) late.

The AADT contribution of the all households on a road e_i to other roads along the shortest path SR_i is $S_{SR_i}(e_i)$,

$$S_{SR_i}(e_i) = \int_0^{l(e_i)} \frac{hh(e_i) \times S}{l(e_i)} dx = hh(e_i) \times S \qquad (7)$$

where $hh(e_i)$ is the household number on e_i, S is the AADT supply rate of each household, and $l(e_i)$ is the length of e_i. The shortest path SR_i to its nearest entrance can be regarded as a vector calculated by Dijkstra's algorithm, and the element e_i is in a subset SR_i of E. After the calculation of $S_{SR_i}(e_i)$, all elements of $\{AADT(e_j)|e_j \in SR_i\}$ are updated by adding $S_{SR_i}(e_i)$, where $AADT(e_j)$ is the AADT of road e_j.
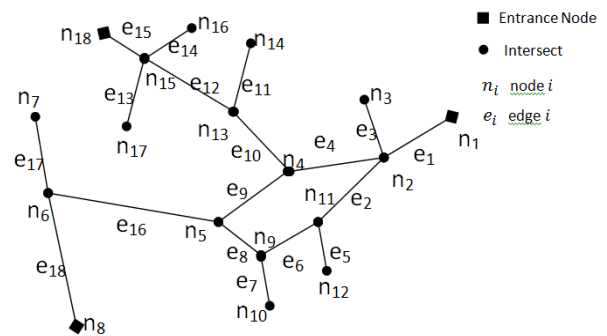

Fig. 3. An example of a community topology

On the other hand, the AADT contribution from road e_i onto itself is different because its starting point s to the entrance is distributed along edge e_i itself. According to the definition of VMT, its AADT contribution of e_i to itself can be calculated as follows:

$$S_{e_i}(e_i) = \int_0^{l(e_i)} [hh(e_i)/l(e_i)]\, Sx dx\, /l(e_i) = hh(e_i)S/2 \qquad (8)$$

It can also be expressed as taking an average at the mid-point of road e_i in view of the even distribution. After the calculation of $S_{e_i}(e_i)$, the $AADT(e_i)$ is updated by adding $S_{e_i}(e_i)$.

When the shortest paths of two nodes of a road are different, it can be to two different entrances as case (ii), or to a same entrance as a rare situation in case (i). Let two nodes of e_i be p_{if} and p_{it} as in Fig. 4. The shortest path from p_{if} to its nearest entrance f is SR_{if}, while the shortest path from p_{it} to its nearest entrance t is SR_{it}. The lengths of these paths are $l(SR_{if})$ and $l(SR_{it})$ respectively as

$$l(SR_{if}) = \sum_{e_j \in SR_{if}} l(e_j) \qquad (9)$$

$$l(SR_{it}) = \sum_{e_j \in SR_{it}} l(e_j) \qquad (10)$$

A key step is to find a balance point p_{ib} on the road, which has a same distance to entrances f and t via SR_{if} and SR_{it},

respectively. The distance from p_{if} to p_{ib} along road e_i is

$$l(e_{i,f-b}) = [l(e_i) - l(SR_{if}) + l(SR_{it})]/2 \qquad (11)$$
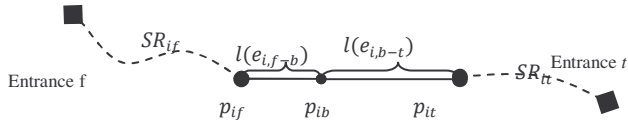

Fig. 4. Balance point

The AADT supplies $S_{SR_{if}}(e_{i,f-b})$ and $S_{SR_{it}}(e_{i,b-t})$ of sub-edges $p_{if} - p_{ib}$ and $p_{it} - p_{ib}$ to their respective paths (excluding edge e_i) are

$$S_{SR_{if}}(e_{i,f-b}) = \int_0^{l(e_{i,f-b})} hh(e_i)S/l(e_i)\,dx$$
$$= hh(e_i)l(e_{i,f-b})S / l(e_i) \qquad (12)$$

$$S_{SR_{it}}(e_{i,b-t}) = \int_0^{l(e_{i,b-t})} hh(e_i)S/l(e_i)\,dx$$
$$= hh(e_i)l(e_{i,b-t})S/l(e_i) \qquad (13)$$

The AADT supply $S_{e_i}(e_i)$ of road e_i to itself is

$$S_{e_i}(e_i) = \frac{\int_0^{l(e_{i,f-b})} \frac{hh(e_i)S}{l(e_i)}x\,dx + \int_0^{l(e_{i,b-t})} \frac{hh(e_i)S}{l(e_i)}x\,dx}{l(e_i)}$$
$$= [l^2(e_{i,f-b}) + l^2(e_{i.b-t})]\,hh(e_i)S/2l^2(e_i) \qquad (14)$$

Notice that

$$l(e_i) = l(e_{i,f-b}) + l(e_{i,b-t}) \qquad (15)$$

It leads to

$$S_{e_i}(e_i) = \left(\frac{1}{2} - \frac{l(e_{i,f-b})}{l(e_i)} + \frac{l^2(e_{i,f-b})}{l^2(e_i)}\right) hh(e_i)S \qquad (16)$$

Now, we present an algorithm to predict the AADT for the shortest path model as the shortest path algorithm:

Step 1. Set $\{\widehat{AADT}(e_i) := 0 | e_i \in E\}$, and initialize traffic supply rate S for each edge $e_i \in E$ in $G = (V, E)$.

Step 2. For each e_i, find the shortest paths SR_{if} and SR_{it} to the nearest entrances for its nodes p_{if} and p_{it} respectively by Dijkstra's algorithm. The SR_{if} and SR_{it} should exclude e_i. Therefore, delete e_i if it is in SR_{if} or SR_{it}.

Step 3. If $SR_{if} = SR_{it}$, go to Step 4, else go to Step 5.

Step 4. Update $\{\widehat{AADT}(e_m), e_m \in SR_{if}\}$ by adding (7), and $\widehat{AADT}(e_i)$ by adding (8). Go to Step 6.

Step 5. Update $\widehat{AADT}(e_i)$ by adding (16). Divide edge e_i into two sub-edges $e_{i,f-b}$ and $e_{i,b-t}$ by (9) and (10) respectively. Update $\{\widehat{AADT}(e_m)\}$ by adding (12) as $e_m \in SR_{if}$ and by adding (13) as $e_m \in SR_{it}$, respectively.

Step 6. Next e_i, and go to Step 2.

After this algorithm is finished, the final set $\{\widehat{AADT}(e_i) | e_i \in E\}$ is the estimated/predicted AADT on each road (edge) $e_i \in E$. It can be used to calculate the lower bound of total

VMT or its equivalent average AADT on this community road network by easy calculation.

5. MODEL WITH TURN PENALTY

As the shortest path model can generate the lower bound for the total VMT of a community, we introduce a modified model with a turn penalty to improve the prediction accuracy. It is from the fact that drivers may usually take routes with less turns if the route lengths are close.

The evaluation function (objective function) for tuning the model is

$$J = \sum_i |\widehat{AADT}(e_i) - AADT(e_i)|, \quad e_i \in SE \qquad (17)$$

where $\widehat{AADT}(e_i)$ is the predicted AADT of road e_i, $AADT(e_i)$ is the sampled AADT of road e_i, and SE is the set of sampled edges (roads). The goal is to minimize J.

This model is developed from the shortest path model by introducing a turning penalty constant T for each turn. If there are n turns in a path to an entrance, the turn penalty is nT. We define a cost function $rc(R)$ of a route R to replace $l(R)$ as

$$rc(R) = l(R) + n \times T \qquad (18)$$

where $l(R)$ is the length of route R. Thus, the shortest path model is a special case of this model as the penalty constant $T = 0$. A turn matrix is introduced as

$$TM = \begin{bmatrix} tm_{11} & \cdots & tm_{1k} \\ \vdots & \ddots & \vdots \\ tm_{k1} & \cdots & tm_{kk} \end{bmatrix}, \quad k = size(E) \qquad (19)$$

$$tm_{ij} = \begin{cases} 1, & \text{a turn from edge } e_i \text{ to edge } e_j \\ 0, & \text{no turn from edge } e_i \text{ to edge } e_j \end{cases} \qquad (20)$$

A least cost algorithm is developed for this model based on the shortest path algorithm. The differences of the former from the later are:

(a) to generate a turn matrix (19), and

(b) to run Dikjstra's algorithm for (18).

In (b), the least cost algorithm further minimizes (i) the route cost (18) for a given T to identify the low cost route R, and (ii) the objective function (17) by adjusting T.

6. PROBABILITY MODEL

This section discusses a probability model. It is based on a fact that every household may drive through each entrance with its probability. This fact is also reflected in our approach formula (4) and (5).

Here, the method is first to calculate the distance (or cost) $C_i(s)$ to each entrance i, then to normalize these v distances as divided by their sum, where v is the number of entrances in the community. Then, an exponential function exp(-Kx) is introduced to transform the normalized distance x to the probability

$$f(x) = \exp(-Kx) \qquad (20)$$

where constant K is tuned to minimize the errors between the estimates and the sampled measurement data in (17). There are many methods available to find an optimal constant K,

e.g., the golden section algorithm, the gradient method, etc.

The steps to calculate possibility for point s are as follows.

(a) Calculate $C_i(s)$, $i = 1, \cdots, v$, from s to entrance i.

(b) Normalize $C_i(s)$ as $\bar{C}_i(s) = C_i/\sum_{i=1}^{v} C_i$, $i = 1,..,v$.

(c) Calculate $f(\bar{C}_i)$, $i = 1, ..., v$, as in (20). Then, further normalize $f(\bar{C}_i)$ as possibility $p_i(s)$ to entrance i as

$$p_i(s) = f(\bar{C}_i)/\sum_{i=1}^{v} f(\bar{C}_i), i = 1, ..., v \qquad (21)$$

An optimal K is searched to minimize (17).

This method can improve the turn penalty algorithm and the shortest path algorithm for the estimation accuracy. Since the shortest path algorithm is a special case of the turn penalty algorithm, we take the turn penalty algorithm for further improvement based on (4) and (5).

Remark 1. The turn penalty algorithm needs to find a best turning penalty constant T. The probability algorithm needs to further find a constant K.

Remark 2. The above algorithms have been implemented by programs on ArcGIS. The developed software can automatically run the mentioned functions and graphs. Due to the page limit, we will describe that in a separate paper.

7. EXPERIMENTS

This section shows our experiment results to validate the models. The inputs to the above algorithms are a set of household numbers on each road (that can be obtained from the database or website) and the initial values of the turn penalty constant T and the constant K. Six communities in Charlotte are selected to tune the model parameters T and K. The total entrance AADT of each community is estimated from the regression (1). Table 1 lists the community information from the GIS and the estimated daily VMT of each community from our different models. The estimated daily VMT by the shortest path model is the smallest among three models as expected, i.e., for the lower bound of the VMT. It is noticed that the large community has large VMT. The last row lists the data of total six communities.

Notice that the common methods apply the sampled average AADT to every road in the group. Thus, Table 2 further compares our three models based on the average AADT. The average AADT on the sampled roads in a selected community is

$$\bar{a} = \sum_{i=1}^{n} a_i/n \qquad (22)$$

where $\bar{a}$ is the average AADT of the sampled roads, n is the number of sample roads in a community, and a_i is the AADT on the i-th sample road, either measured or estimated. The relative error between the estimated and measured average AADTs is used to evaluate the accuracy

$$Err = |\bar{a}_e - \bar{a}_m|/\bar{a}_m \qquad (23)$$

where $\bar{a}_e$ is the estimated average AADT, and $\bar{a}_m$ is the measured average AADT on the sampled roads. The last row listed as "total" is calculated on all sample roads in six communities as a group.

From the last row of Table 2, we observe that the accuracy of

probability model is better than other two, if appropriate probability constant K and turn penalty constant T are chosen.

We now check and compare the prediction accuracy of our models and the common method. As mentioned above, the common method applies the sampled average AADT, e.g., 723.83 from communities 1-6, to all other un-measured roads in the group. Therefore, we select another two communities for comparison. Our models also use the same parameters from communities 1-6. The experiment results on the selected another two communities are listed in Table 3. The test results show that our model method is much better than the common method in the experiments for the prediction.

The data shows that the probability model is more accurate than another two models. On the other hand, it has two parameters to be determined, that may make it more difficult to search.

8. CONCLUSIONS

In this paper, the linear relationship between the total entrance AADT and the household number of a community is revealed. Based on this relationship and the road topology, we present three community traffic models to estimate and predict the AADT and VMT on community road networks. It provides an approach to solve a long-time existing problem for the AADT and VMT estimate on community road networks which lack the monitoring systems. Finally, the experiment results show that the models have certain accuracy. The methods are valid and may be used in the AADT and VMT estimation and prediction on local roads networks for further tests. The new methods have advantages of labor saving. Also, the automatic software estimation is compatible to the GIS without the requirement of the monitoring system.

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Table 1. VMT and other data of each community

Community Number	Estimated Daily VMT (miles/d)			Number of Households	Number of road Sections	Number of Sampled Sections
	Shortest Path Model	Model with Turn Penalty T=83	Probability Model with T=83 and K=24			
1	2279.05	2310.08	2336.01	493	61	6
2	1459.87	1460.19	1522.28	482	55	5
3	790.44	867.13	802.95	200	29	6
4	862.52	862.69	868.34	171	24	4
5	394.99	395.18	397.94	125	22	4
6	358.58	358.58	360.79	107	18	5
Total 1 – 6	6145.46	6253.86	6288.31	1578	209	30

Table 2. Average AADT of the sampled roads from the measurement and the model estimation

Community number	Sampled Average AADT	Shortest Path Model		Model with Turn Penalty T=83		Probability Model with T=83 and K=24	
		Average AADT	Relative Error	Average AADT	Relative Error	Average AADT	Relative Error
1	1056.83	1117.00	5.69%	1016.18	3.85%	1030.36	2.50%
2	1337.00	1331.03	0.45%	1330.68	0.47%	1300.04	2.76%
3	472.50	424.76	10.10%	425.17	10.02%	426.40	9.76%
4	807.00	754.47	6.51%	755.54	6.38%	761.01	5.70%
5	378.75	458.59	21.08%	455.53	20.27%	455.28	20.21%
6	222.20	320.67	44.32%	320.67	44.32%	321.69	44.78%
Total 1 – 6	723.83	745.38	2.98%	724.97	0.16%	723.81	2.76 e-5

Table 3. Comparison of methods on Average AADT of the sampled roads in two test communities

Community number	Number of measured Test points	Sampled Average AADT	Shortest Path Model		Model w. Turn Penalty		Probability Model		Common Method	
			Average AADT	Relative Error	Average AADT	Relative Error	Average AADT	Relative Error	Average AADT	Relative Error
7	9	1094.78	1044.77	4.57%	1112.91	4.78%	1112.91	1.66%	723.83	33.88%
8	11	1892.46	1352.14	28.55%	1352.26	28.54%	1367.56	27.74%	723.83	61.75%
Total 7 & 8	20	1533.50	1213.83	20.85%	1212.84	20.91%	1252.97	18.29%	723.83	52.80%