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Estimating intersection turning volumes from actuated traffic signal information

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ABSTRACT

Actuated traffic signals usually use loop detectors. The current practice in many cities is to install four consecutive loop detectors in each lane to reduce the chance of undetected vehicles. Due to practical reasons, all four loop detectors in each lane and other detectors referring to the same phase are spliced together. Thus, it is possible for several vehicles to be counted as one single car. This way of detector wiring to the cabinet reduces the accuracy of detectors for collecting traffic volumes. Our preliminary studies show cases with an error greater than 75 percent. Therefore, the purpose of this paper is to provide a simple method to obtain turning volumes from signal information in actuated non-coordinated traffic signals without using loop detector data. To produce the required data, a simulation was performed in VISSIM with different input volumes. To change turning volumes, a code was developed in COM interface. With this code, the inputs did not have to be changed manually. In addition, the COM code stored the outputs. Data were then exported to a single Excel file. Afterwards, regression and the adaptive neural fuzzy inference system (ANFIS) were used to build models to obtain turning volumes. The accuracy of models is defined in terms of mean absolute percent error (MAPE). Results of our two case studies show that during peak hours, there is a high correlation between actuated green time and volumes. This method does not need extensive data collection and is easy to be employed. The results also show that ANFIS produces more accurate models compared to regression.

1. Introduction

Traffic volume studies are conducted to determine the number, movements, and classifications of roadway vehicles at a given location. This data helps identify critical flow time periods and determine the influence of large vehicles or pedestrians on vehicular traffic flow. Manual counts are typically used to gather data for determination of vehicle classifications, turning movements, direction of travel, and vehicle occupancy. Most applications of manual counts require small samples of data at any given location.

The automatic count method provides a means for gathering large amounts of traffic data using permanent or

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portable counters. The majority of signalized intersections operate under some form of actuated control, and in that intersection approaches (or lanes) have some type of inductive loops. The new loop detector (also called loop amplifier) and signal controller equipment now provide the ability to collect traffic count information from the same loops used for actuated controls on intersection approaches. The potential to extract traffic counts from an existing signalized intersection loop detection system provides the opportunity to collect data with minimal costs. There are many benefits of collecting traffic counts from loops at signalized intersections including the low cost. However, there are also several issues that reduce loop detector accuracy and reliability for collecting automatic turning volumes, including variations among transportation agencies in terms of signal loop placement, layout and wiring, potential variations in methods of data extraction based upon the type of technology and/or detector manufacturer used, and loop maintenance issues.

This paper tries to provide a simple method to obtain turning volumes from signal information in actuated non-coordinated traffic signals without using loop detector data. The two case study intersections are located in Reno, Nevada. Because of simplicity, this method can be used in agencies without any other equipment or changing the loop system configuration.

2. Literature review

Very few efforts are reported in regard to the use of local traffic detectors for systematic volume data collection. Some researchers have investigated freeway loop detector errors (Chen et al., 2007; Chen and May, 1987; Dailey, 1993; Jacobson et al., 1990; May et al., 2004; May et al., 2005; Middleton et al., 2006; Nihan, 1997; Nihan et al., 1990; Payne and Thompson, 1997; Rajagopal and Varaiya, 2007; Vanajakshi and Rilett, 2004). However, due to the significance of speed and space, headway of vehicles on loops and freeway detecting loops have different characteristics and accuracy compared to intersection loops. Some cities, including Seattle, San Antonio, and Toronto provide real-time or stored travel information on selected freeways and arterials based on information received at their traffic management centers from their network of inductive loop detectors.

Metropolitan Toronto reported the development of a prototype transit and traffic information system (Berinzon, 1993). The goal was to incorporate freeway and arterial SCOOT data into a complete user information data system. The system is called COMPASS and is employed on some sections of the Queen Elizabeth Way (QEW) and Highway 401 (Turner et al., 1999). In this system, data is collected at 20 s intervals and aggregated to 5 min, 15 min, 1 h, daily and monthly time periods. Volume, occupancy and speed data are archived for the 20 s and 5 min time intervals while only volume data is archived.

The San Antonio TransGuide program has been warehousing traffic information from over 300 detector stations located on freeway mainline segments and ramps. Speed, volume, and occupancy data are all stored in their database (Turner et al., 1999).

Institute of Transportation Engineers (ITE) reports that four cities, Nashua, NH; Fremont, CA; Minneapolis/St. Paul, MN; and Bellevue, WA are collecting traffic counts using their loop detector systems (ITE Traffic Engineering Council, 2007).

Nashua has mostly National Electrical Manufacturer's Association (NEMA) Standard TS1 cabinets. The initial thought for collecting data at one intersection was to utilize the present loops at the STOP line of all approaches. These loops were known to be working after detailed testing by the city's maintenance and operations staff. However, after reviewing the signal layout plans for the intersection and comparing the functionality of available upstream 6 ft by 6 ft system loops with the present loops, the conclusion was made to use the system loops. Data was extracted from the controller using a field laptop every 10 d during the desired data collection period (ITE Traffic Engineering Council, 2007).

In Fremont, CA, data was collected from the system loops and stored in and managed by the traffic signal controller. The controller was programmed to configure each system loop and determine how the collected data is grouped. Loops were typically set up to collect traffic volume and occupancy data, which were summarized in 15 min intervals, very similar to traditional tube counts for collecting average daily traffic. Fremont has standardized its traffic signals with the use of National Electrical Manufacturers Association's (NEMA) TS2 traffic signal controllers and controller cabinets (ITE Traffic Engineering Council, 2007).

In 1993, the Minnesota Department of Transportation (Mn/DOT) began collecting loop detector counts on the instrumented part of the Twin Cities metropolitan freeway System. The system now consists of 648 directional miles and 4300 inductive loop detectors. Both volume and occupancy were recorded and achieved in 30 s intervals. Loop detector data from traffic signals has always been available using the signal controller proprietary software, but the data was difficult to retrieve and analyze. In 2005, Mn/DOT began retrieving loop detector data from the field, and then storing the data in a format that could be easily analyzed. The data was stored on a server in binary format that could be retrieved by anyone at Mn/DOT. Tools were developed to allow the users to retrieve data for numerous loop detectors over a given period (hours to months). This data can then be averaged, smoothed, and graphed.

Bellevue, WA, also similar to Nashua and Fremont, used advanced loops located about 100–140 ft from the STOP line to measure the volume and occupancy data of an approach. If the approach roadway had more than one lane, the combined traffic flow of that approach was measured. At some locations with heavy turning volumes or uneven lane distribution, separate measurements for each movement were made. A remote communication unit in the signal cabinet transmitted the raw data back to the central signal computer in the TMC (ITE Traffic Engineering Council, 2007).

North Carolina conducted a test at several locations in the state and concluded that there was a high level of similarity between manual counts and the 6 ft by 6 ft stretch loop counts. Therefore, they recommended that North Carolina begin using stretch (far) loops for traffic counts by rewiring cabinets and installing detector amplifiers with count outputs on an as-needed basis. They did not recommend the use of

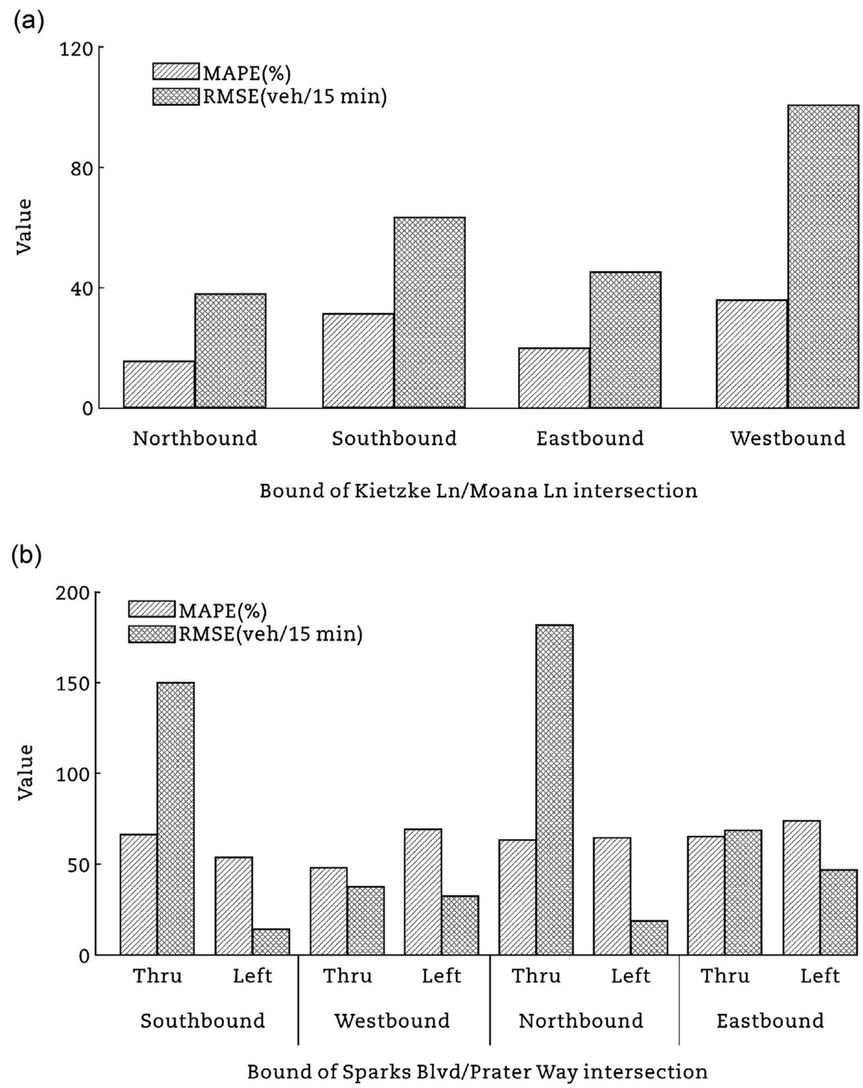


Fig. 1 – MAPE (%) and RMSE (veh/15 min). (a) Kietzke/Moana intersection, Reno. (b) Sparks/Prater intersection, Sparks.

quadrupoles. NCDOT does not need to replace every detector amplifier with count-output units; rather, it can simply swap them out as needed for counts. Finally, they essentially observed no variation between rhombus, diamond, and square shaped loops during their 2001 field investigation, but it recommended that North Carolina retains the use of rectangular (square) 6 ft by 6 ft loop shapes (Milazzo et al., 2001).

Several researchers have studied accuracy of loop detector counts and improvement algorithms. Vanajakshi and Rilett (2004) and Bender and Nihan (1988) reviewed studies regarding the accuracy of loop detector counts and improvement algorithms. Jacobson et al. (1990) divided loop detector data screening tests into two main categories: microscopic and macroscopic. At the microscopic level, detector pulses were scanned and checked for errors in the field. At the macroscopic level, the volume from detectors was collected from the sites and was compared with manual counts. Some researchers have addressed loop detector data errors, it's causes, and effects (Bikowitz and Ross, 1985; Chen and May, 1987; Courage et al., 1976; Dudek et al., 1974; Pinnell, 1976). Studies of loop detector data errors at the microscopic level usually require reprogramming or modification of the detector device and depend on the type of loop detector (Chen and May, 1987; Coifman, 1999; Nihan et al., 1990). However, macroscopic approaches are more commonly adopted because they are independent of the sensor type and are carried out at the data processing level (Peeta and Anastassopoulos, 2002). Common macroscopic studies compare volumes, occupancies, or speeds with specific threshold values (Cleghorn et al., 1991; Jacobson et al., 1990; Payne and Thompson, 1997). The main disadvantage of single-parameter threshold tests, which typically consider only one parameter at a time, is that they assume the acceptable range for a parameter is independent of the values of the other parameters. Because combinations of parameters are not tested, single-parameter threshold tests cannot identify unreasonable combinations. Typically, the combinations of parameter tests take advantage of the relationships among the three parameters: mean speed, volume, and occupancy (Cleghorn et al., 1991; Coifman and Dhoorjaty, 2002; Jacobson et al., 1990; Payne and Thompson, 1997; Turner et al., 2000; Turochy and Smith, 2000).

Based on our researches, all these approaches used detector data for determining turning movements. However, it will be shown in the next section that detector data is not a reliable source for estimating turning movement volumes in many cases. As a result, it is usually recommended to change the loop or wiring configuration which is very costly. This paper proposes a method for obtaining automated turning movement volumes, which does not need detector data and relies only on signal log data.

3. Problem statement

The best source to obtain intersection turning volumes is signal-controlling detectors. They are in place for operation of the signals so they can be used for obtaining counts without any extra cost. ITE report proves that loop detectors can produce excellent counts if location and wiring of loops are appropriate (ITE Traffic Engineering Council, 2007). However, they usually do not have these ideal configurations and as a result, count errors are significant. To show the accuracy of loop detectors for collecting turning movement counts, a study was conducted on two intersections in Reno and Sparks, NV. Accuracy of detectors can be expressed using one of the following two error quantity values (Middleton et al., 2006).

(1) Mean absolute percent error (MAPE) (Eq. (1)).
(2) Root mean squared error (RMSE) (Eq. (2)).

$$\mathrm{MAPE} = \frac{\sum_{i=1}^{n}\left|\frac{D_i - B_i}{B_i}\right|}{n} \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(D_i - B_i)^2}{n}} \tag{2}$$

where MAPE is mean absolute percentage error, RMSE is root mean squared error, D_i is detector data value, B_i is reference (base) data value, n is total number of intervals.

Detector data (D_i) is obtained from detector logs in data bases of city of Reno and city of Sparks. Reference (base) data (B_i) is obtained from manual counting. The data intervals are 15 min counts and are obtained during peak hours of morning, noon, and afternoon. The total number of intervals (n) is 24.

At the Kietzke Ln and Moana Ln intersection in Reno, MAPE is up to 35% and in the Sparks intersection (Sparks Blvd and Prater Way), it is up to 75% (Fig. 1). RMSE in this figure is vehicle per 15 min (veh/15 min). In the Reno intersection, RMSE is as high as 100 veh/15 min and in Sparks, it is up to 180 veh/15 min. These measures show very high errors that indicate loop detectors are not reliable for obtaining turning movements. The main reason of detector errors is the way detectors are wired. Both cases in Reno and Sparks have four consecutive loops at stop bar which are spliced together. This means one set of four connected loops counts only one vehicle when several vehicles are on them at the same time. Therefore especially during peak hours this configuration, which is a very common practice, counts less vehicles.

The unreliability of loop detectors for producing turning movements was the incentive to develop a method to obtain automated intersection turning volumes without using detector data. Except from detectors, the only remaining source of available automated data is signal logs. Fig. 2 shows a signal log sample from the intersection of Virginia St and McCarran Blvd in Reno, NV. Table 1 also shows the signal configuration for this intersection. The following sections will answer this research question: Can turning volumes be estimated based on this signal information without using loop detector data?

Split History 7/17/2014

ID: 164
Name: VIRGINIA & MCCARRAN NORTH
Begin Date/Time: 06/23/2014 12:00 am **End Date/Time:** 06/23/2014 11:59 pm

DateTime	Pattern	Cycle	SP1	SP2	SP3	SP4	SP5	SP6	SP7	SP8	SP9	SP10	SP11	SP12	SP13	SP14	SP15	SP16
6/23/2014 00:16 AM	254	34	12	10	0	12	0	22	0	12	0	0	0	0	0	0	0	0
6/23/2014 00:17 AM	254	22	0	11	0	11	0	11	0	11	0	0	0	0	0	0	0	0
6/23/2014 00:17 AM	254	24	0	11	0	13	0	11	0	13	0	0	0	0	0	0	0	0
6/23/2014 00:18 AM	254	38	0	11	15	12	0	11	16	11	0	0	0	0	0	0	0	0
6/23/2014 00:18 AM	254	31	0	16	0	15	0	16	0	15	0	0	0	0	0	0	0	0
6/23/2014 00:19 AM	254	36	0	12	0	24	0	12	12	12	0	0	0	0	0	0	0	0
6/23/2014 00:20 AM	254	25	0	10	0	15	0	10	0	15	0	0	0	0	0	0	0	0
6/23/2014 00:20 AM	254	23	0	12	0	11	0	12	0	11	0	0	0	0	0	0	0	0
6/23/2014 00:20 AM	254	34	0	11	12	11	0	11	0	23	0	0	0	0	0	0	0	0
6/23/2014 00:21 AM	254	45	11	11	11	12	0	22	0	23	0	0	0	0	0	0	0	0
6/23/2014 00:22 AM	254	24	0	12	0	12	0	12	0	12	0	0	0	0	0	0	0	0
6/23/2014 00:22 AM	254	36	0	13	0	23	0	13	12	11	0	0	0	0	0	0	0	0
6/23/2014 00:23 AM	254	27	0	11	0	16	0	11	0	16	0	0	0	0	0	0	0	0
6/23/2014 00:23 AM	254	24	0	11	0	13	0	11	0	13	0	0	0	0	0	0	0	0
6/23/2014 00:23 AM	254	23	0	11	0	12	0	11	0	12	0	0	0	0	0	0	0	0
6/23/2014 00:24 AM	254	24	0	12	0	12	0	12	0	12	0	0	0	0	0	0	0	0
6/23/2014 00:24 AM	254	24	0	11	0	13	0	11	0	13	0	0	0	0	0	0	0	0
6/23/2014 00:25 AM	254	23	0	11	0	12	0	11	0	12	0	0	0	0	0	0	0	0
6/23/2014 00:25 AM	254	34	0	10	0	24	0	10	12	12	0	0	0	0	0	0	0	0

Fig. 2 – Signal log from intersection of Virginia St and McCarran Blvd, Reno, NV.

Table 1 – Signal configuration of intersection of Virginia St and McCarran Blvd, Reno, NV.

ID: 164

Name: Virginia & McCarran North

Configuration: Standard

Param	Phs 1	Phs 2	Phs 3	Phs 4	Phs 5	Phs 6	Phs 7	Phs 8
Walk	0.0	7.0	0.0	7.0	0.0	9.0	0.0	8.0
Ped clearance	0.0	20	0.0	25.0	0.0	30.0	0.0	22.0
Min green	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0
Passage	2.5	3.0	2.5	3.0	2.5	3.0	2.5	3.0
Max1	38.0	38.0	39.0	32.0	28.0	39.0	38.0	32.0
Max2	23.0	19.0	27.0	37.0	19.0	23.0	19.0	37.0
Yellow	3.0	4.3	3.0	4.7	3.0	4.3	3.0	4.7
Red	1.0	0.5	1.0	1.0	1.0	0.5	1.0	1.0
Red revert	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0
Added initial	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Max initial	4.0	6.0	4.0	6.0	4.0	6.0	4.0	6.0
Time before reduce	4.0	6.0	4.0	6.0	4.0	6.0	4.0	6.0
Cars before reduce	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Time to reduce	21.0	23.0	23.0	18.0	15.0	23.0	23.0	18.0
Reduce by	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Min gap	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5
Dynamic max limit	48.0	65	60.0	42.0	38.0	65.0	50.0	42.0
Dynamic max step	10.0	5.0	10.0	5.0	5.0	5.0	10.0	5.0
Startup	RED	RED	RED	GREEN	RED	RED	RED	GREEN
Enable	On	On	On	On	On	On	On	On
Auto entry	Off	Off	Off	On	Off	Off	Off	On
Auto exit	Off	Off	Off	On	Off	Off	Off	On
Non act1	Off	Off	Off	Off	Off	Off	Off	Off
Non act2	Off	Off	Off	Off	Off	Off	Off	Off
Lock call	Off	Off	Off	Off	Off	Off	Off	Off
Min recall	Off	On	Off	On	Off	On	Off	On
Max recall	Off	Off	Off	Off	Off	Off	Off	Off
Ped recall	Off	Off	Off	Off	Off	Off	Off	Off
Soft recall	Off	Off	Off	Off	Off	Off	Off	Off
Dual entry	Off	Off	Off	Off	Off	Off	Off	Off
Sim gap enable	Off	Off	Off	Off	Off	Off	Off	Off
Guar passage	Off	Off	Off	Off	Off	Off	Off	Off
Rest in walk	Off	Off	Off	Off	Off	Off	Off	Off
Cond service	Off	Off	Off	Off	Off	Off	Off	Off
Add init calc	Off	Off	Off	Off	Off	Off	Off	Off
Ring	1.0	1.0	1.0	1.0	2.0	2.0	2.0	2.0

4. Methodology

The methodology of estimating intersection turning volumes from traffic signal information is shown in Fig. 3. To produce the required data, a simulation should be performed in VISSIM. The reason for choosing this software is its ability to produce high-resolution outputs that are required in this method. In this simulation, turning volumes from 50 to 1250 vph with the interval of 100 were entered for each signal configuration parameter. To change turning volumes, a code was developed in COM interface. With this code, the inputs do not have to be changed manually. A sample of VISSIM output is shown in Fig. 4. In this output for each phase, one column shows the state of signal (green by |, yellow by ⟍, and red by a dot) and other columns show the state of detectors (occupied by? and otherwise by a dot). Then, for each phase, all green times and their corresponding volume should be extracted. Each row in this data set includes traffic volume passing by during green time (gt), cycle length (cl), minimum green (mg), vehicle extension (ve), min recall (discrete variable with yes or no as values), max recall (discrete variable with yes or no as values), and side street traffic volume (sv). Because side street hourly volume (sv) is unknown in reality, time of day or different time intervals regarding traffic condition (i.e. night, off-peak, and peak) should be replaced with this variable. Table 2 shows a sample of the prepared data set. In this table, some variables are removed because they are the same for all the data set. For example, minimum green (mg) is not usually necessary because it does not change during different times. The next step is to make a model for each phase/movement. For the model, the green time volume (gv) is selected as a dependent variable while the other parameters are defined as independent variables. Afterwards, a prediction model is built for each phase/movement. Two methods were adopted to build the models: regression and adaptive neural fuzzy inference system (ANFIS). ANFIS is a class of adaptive networks that is

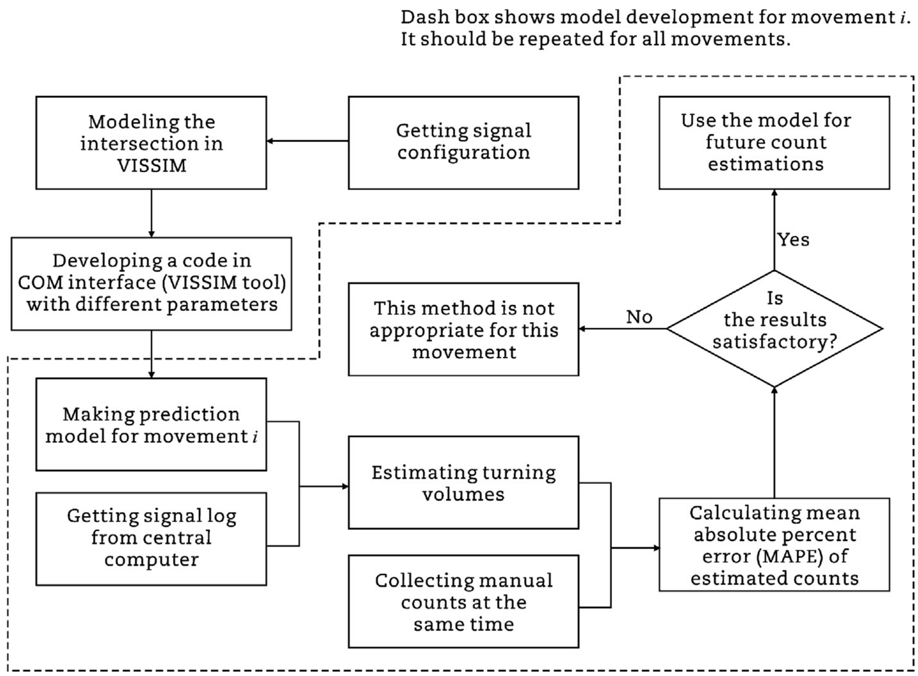


Fig. 3 – Methodology of estimating intersection turning volumes from traffic signal information.

functionally equivalent to fuzzy inference system; however, in ANFIS, the user does not need to define the rules. Rules are generated using an artificial neural system. In this study, the ANFIS built in function of MATLAB was used. VISSIM outputs are used for training and manual counts for validating. The following section explains the ANFIS approach briefly. A detailed description and discussion can be found in Negnevitsky (2004) and Yen and Langari (1999).

4.1. *ANFIS*

ANFIS combines the fuzzy inference system (FIS) and artificial neural networks (ANN) where the FIS is used to model relationship between non-linear variables and ANN is used to optimize input and output membership function parameters. FIS can be defined as a process of mapping from a given input to an output using the theory of fuzzy sets and ANN is an artificial neural network that consists of a number of very simple and highly interconnected processors, also called neurons. The neurons are connected by weighted links passing signals from one neuron to another. ANN adjusts the weights to bring the network input/output behavior into line with that of the training data. There are two well-known fuzzy inference system: Mamdani-style inference and Sugeno-style inference (Negnevitsky, 2004). The Sugeno fuzzy model was used for a systematic approach to generating fuzzy rules from a given

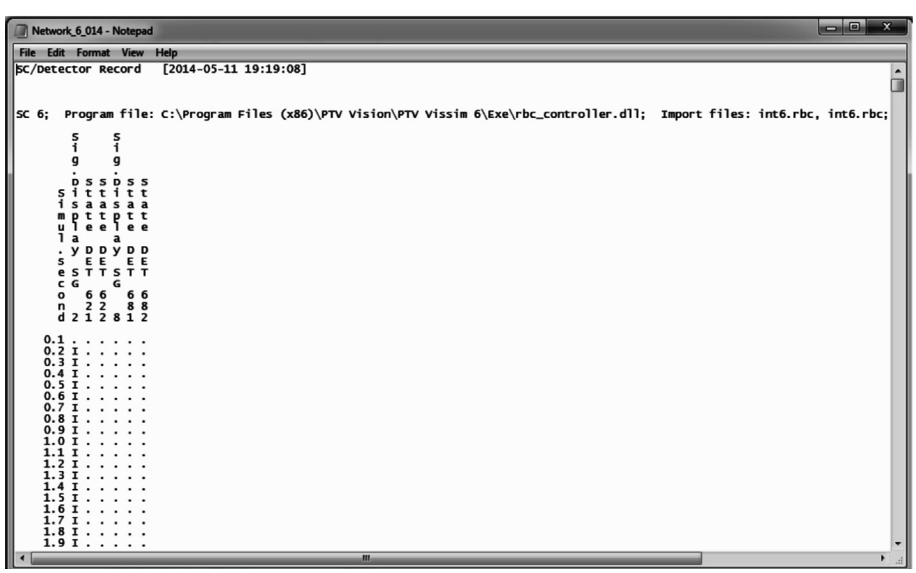


Fig. 4 – Sample of VISSIM output for phases 2 and 8.

Table 2 – A sample of signal information from VISSIM simulation.

Cycle No.	Green time	Volume per cycle	Hourly volume
1	20.6	12	Night
2	20.7	12	Night
3	20.7	12	Night
⋮	⋮	⋮	⋮
12,373	18.6	8	Peak
12,374	14.8	7	Peak
12,375	13.0	6	Peak

input–output data set. A typical Sugeno fuzzy rule can be expressed as follows

IF	Green time	is	Medium
AND	Minor (intersecting) street volume (time intervals)	is	Peak-hour
THEN	Green time volume	is	High

The ANFIS adopted in this paper is represented by a six-layer feedforward neural network (Negnevitsky, 2004). Fig. 5 shows the ANFIS architecture that corresponds to the first-order Sugeno fuzzy model.

Layer 1 is the input layer. Neurons in this layer simply pass external crisp signals to Layer 2. That is,

$$y_i^{(1)} = x_i^{(1)} \tag{3}$$

where $x_i^{(1)}$ is the input, $y_i^{(1)}$ is the output of input neuron i in Layer 1.

Layer 2 is the fuzzification layer. Neurons in this layer perform fuzzification. For sake of simplicity of diagram, Fig. 5 shows only two fuzzy members for each variable. For example, two fuzzy members of variable green time (x_1) can be defined as Low (A1) and High (A2). B1 and B2 are also different levels for variable minor street volume (x_2). However, the actual members for both variables are more than two. In this paper, for fuzzification neurons, bell activation function and trapezoid activation function were tested.

A bell activation function, which has a regular bell shape, is specified as

$$y_i^{(2)} = \frac{1}{1+\left(\frac{x_i^{(2)}-a_i}{c_i}\right)^{2b_i}} \tag{4}$$

where $x_i^{(2)}$ is the input and $y_i^{(2)}$ is the output of neuron i in Layer 2, a_i, b_i and c_i are parameters that control the center, width and slope, respectively, of the bell activation function of neuron i. Trapezoid activation function is specified by its four corners.

Layer 3 is the rule layer. Each neuron in this layer corresponds to a single Sugeno-type fuzzy rule. A rule neuron receives inputs from the respective fuzzification neurons and calculates the firing strength of the rule it represents. In an ANFIS, the conjunction of the rule antecedents is evaluated by the operator product. Thus, the output of neuron i in Layer 3 is obtained as follow

$$y_i^{(3)} = \prod_{j=1}^{k} x_{ji}^{(3)} \tag{5}$$

where $x_{ji}^{(3)}$ is the input and $y_i^{(3)}$ is the output of rule neuron i in Layer 3.

$$y_{\Pi 1}^{(3)} = \mu_{A1} + \mu_{B1} = \mu_1 \tag{6}$$

where the value of μ_1 represents the firing strength, or the truth value, of rule 1, which refers the first rule of the Layer 3.

Layer 4 is the normalization layer. Each neuron in this layer (N1 – N4) receives inputs from all neurons in the rule layer and calculates the normalized firing strength of a given rule. The normalized firing strength is the ratio of the firing strength of a given rule to the sum of firing strengths of all rules. It represents the contribution of a given rule to the final result.

Thus, the output of neuron i in Layer 4 is determined as follow

$$y_i^{(4)} = \frac{x_i^{(4)}}{\sum_{j=1}^{n} x_{ji}^{(4)}} = \frac{\mu_i}{\sum_{j=1}^{n}\mu_j} = \overline{\mu_i} \tag{7}$$

where $x_{ji}^{(4)}$ is the input from neuron j located in Layer 3 to neuron i in Layer 4, n is the total number of rule neurons.

For example

$$y_{N1}^{(4)} = \frac{\mu_1}{\mu_1+\mu_2+\mu_3+\mu_4} = \overline{\mu_1} \tag{8}$$

Layer 5 is the defuzzification layer. Each neuron in this layer is connected to the respective normalization neuron and also receives initial inputs, x_1 and x_2. A defuzzification neuron calculates the weighted consequent value of a given rule as follow

$$y_i^{(5)} = x_i^{(5)}(k_{i0} + k_{i1}x_1 + k_{i2}x_2) = \overline{\mu_1}(k_{i0} + k_{i1}x_1 + k_{i2}x_2) \tag{9}$$

where $x_i^{(5)}$ is the input and $y_i^{(5)}$ is the output of defuzzification neuron i in Layer 5, k_{i0}, k_{i1}, and k_{i2} are the set of consequent parameters of rule i.

Layer 6 is represented by a single summation neuron. This neuron calculates the sum of outputs of all defuzzification neurons and produces the overall ANFIS output, y.

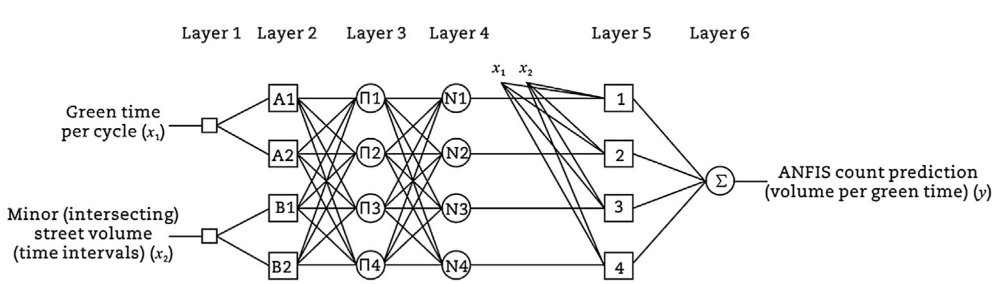


Fig. 5 – ANFIS.

$$y = \sum_{i=1}^{n} x_i^{(6)} = \sum_{i=1}^{n} \overline{\mu_1}(k_{i0} + k_{i1}x_1 + k_{i2}x_2) \quad (10)$$

It is often difficult or even impossible to specify a rule consequent in a polynomial form. Conveniently, it is not necessary to have any prior knowledge of rule consequent parameters for an ANFIS to deal with a problem. An ANFIS learns these parameters and tunes membership functions.

4.2. *Count estimation procedure*

After making the models for each phase/turning movement, green time of signal logs would be used as the input of the models (Fig. 2). For each green time, models estimate a volume. Then these volumes can be summed up to produce 15 min or hourly counts.

To verify the models for each phase, real turning volumes are compared with model outputs. The detector accuracy is defined in terms of MAPE. Then if MAPEs are satisfactory, models can be used for future turning movement estimations.

5. Case studies

The intersection of E 2nd St (east–west, as major street) and Kirman Ave (north–south, as minor street) (Fig. 6), and the intersection of McCarran Blvd (east–west) and N Virginia St (north–south) in Reno, NV (Fig. 7) were selected for case studies. The first intersection represents a major–minor intersection and the second one represents a major–major intersection. Fig. 8 shows scatter plots of green time per cycle and volume per cycle at E 2nd St during different times. Twenty four hours were categorized into five different time intervals from very low volume, which refers to midnight hours, to very high volume, which refers to peak hours. This figure shows that during off-peak hours, there is not a high correlation between actuated green time and volumes. This is because the signal continues in green time until max green and a call from the side street. Close to peak hours, the flow rate becomes closer to saturation flow rate and green time shows more correlation with volume. During

Fig. 6 – Intersection of E 2nd St (east–west) and Kirman Ave (north–south), Reno, NV.

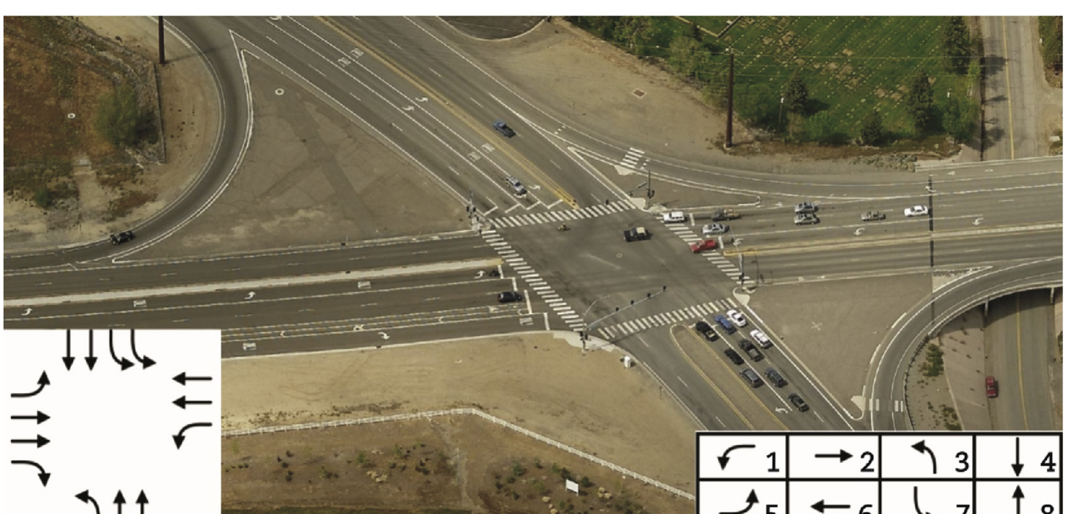


Fig. 7 – Intersection of McCarran Blvd (east–west) and N Virginia St (north–south), Reno, NV.

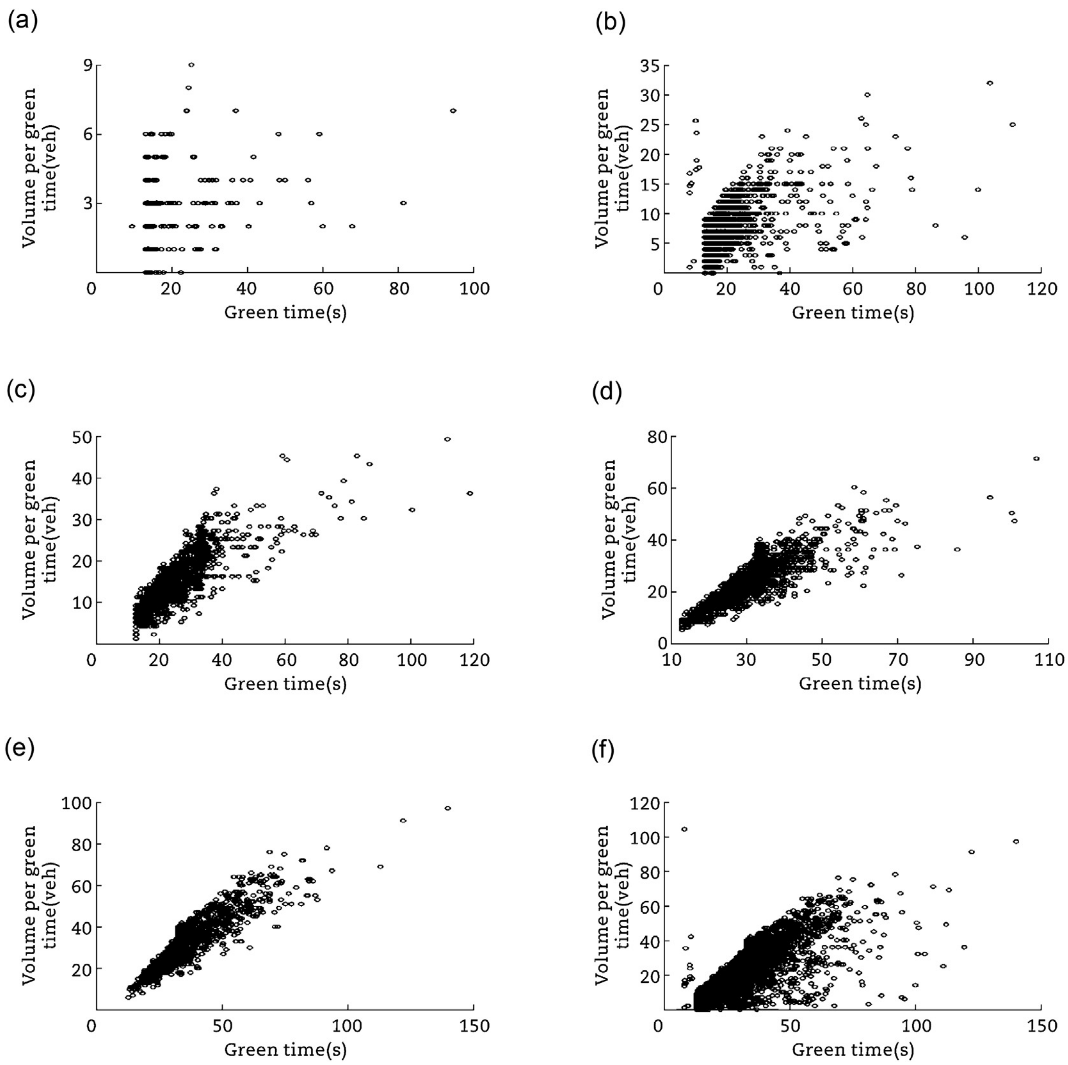


Fig. 8 – Scatter plot of green time per cycle and volume per cycle in E 2nd St during different times. (a) Very low volume. (b) Low volume. (c) Medium volume. (d) High volume. (e) Very high volume (peak hour). (f) All times.

peak hours, there are enough calls from the side street to terminate green after gap out on the major street. Therefore, almost in all cycles, a certain number of vehicles can pass through the intersection within a given green time before gap out happens. In the side street, because green terminates after gap out or maximum green, there is high association between green time and volume at all times.

Similar scatter plots were produced for the intersection of McCarran Blvd. and N Virginia St However, in this intersection, both streets are major streets and therefore, it is only during peak hours or close to peak hours that green time shows correlation with volume. Section 6 describes the results of applying the proposed method on these intersections.

6. Results

Table 3 demonstrates a sample of fuzzy sets of variable green time for the intersection of McCarran Blvd and Virginia St during peak hours. The name above each trapezoid means the number of variable and membership function. Intersecting street volume was not significantly improving the results. Therefore, for sake of simplicity, it was omitted from the modeling process. There are applications that can be used to facilitate the usage of ANFIS models. One of them is anfisedit graphical user interface (GUI) in MATLAB. For each approach, all information of fuzzy sets should be entered into anfisedit GUI. Both bell shaped and trapezoid membership functions were tested for approaches. Bell shaped membership functions, despite of their complexity, could not make models significantly better than trapezoid membership function. In Table 3, all phases have four members in their fuzzy sets. Having four members means each variable has been categorized into four categories that are: very low, low, medium, and high. The numbers inside the brackets show the four corners of trapezoid members. For example, member medium in Phase 1 has been defined by 17.30, 23.46, 27.55, and 30.72. This means that membership of volumes less than 17.30 and bigger than 30.72 are zero in this category, and one from 23.46 to 27.55. Other volume ranges have a membership between zero and one.

Table 3 – Sample of fuzzy sets of intersection McCarran Blvd and Virginia St during peak hours.

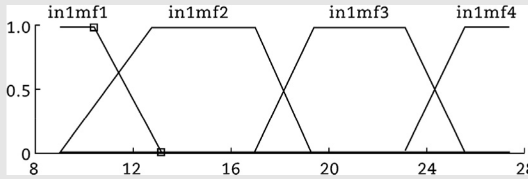
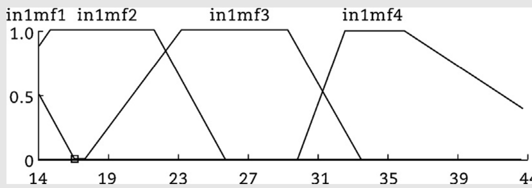
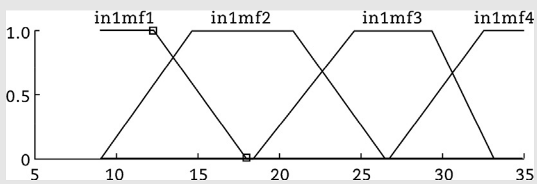
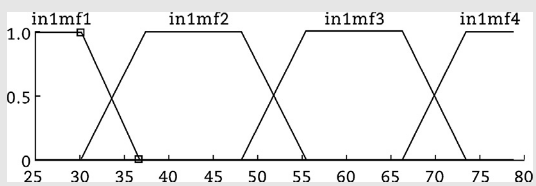
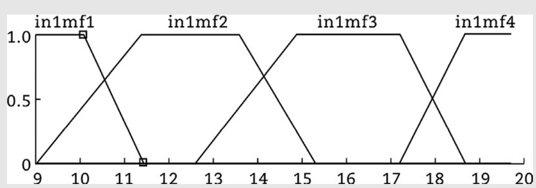
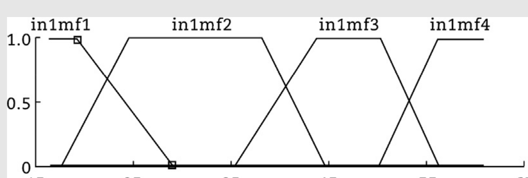
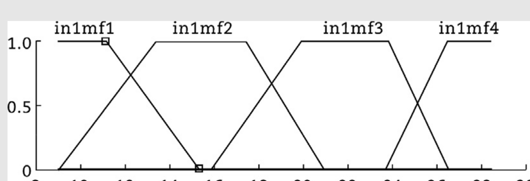
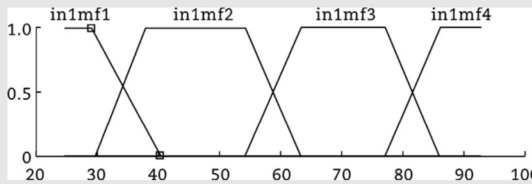
Phase	Membership functions	Parameters
1		[3.747 6.920 12.610 16.840] [10.14 15.05 20.60 24.60] [17.30 23.46 27.55 30.72] [27.59 30.72 35.48 38.65]
2		[3.747 6.920 12.610 16.700] [10.21 15.21 21.19 25.20] [17.30 23.07 29.39 33.71] [29.40 32.10 35.48 46.53]
3		[2.91 6.39 12.30 18.04] [9.00 14.68 20.96 26.50] [18.35 24.70 29.50 33.26] [26.77 32.64 37.71 41.19]
4		[12.03 19.27 30.20 36.70] [30.13 37.43 48.23 55.46] [48.23 55.47 66.33 73.57] [66.33 73.57 84.43 91.67]
5		[6.503 7.930 10.080 11.430] [8.999 11.390 13.580 15.270] [12.57 14.88 17.22 18.66] [17.20 18.64 20.77 22.20]
6		[6.117 12.050 19.420 29.180] [17.78 24.66 38.34 44.70] [35.44 43.87 50.36 56.40] [50.21 56.30 65.45 71.38]
7		[4.45 7.05 11.11 15.34] [9.001 13.400 17.490 20.990] [15.88 19.93 23.87 26.57] [23.71 26.48 30.45 33.05]

Table 3 – (continued)

Phase	Membership functions	Parameters
8		[8.81 17.89 29.32 40.38] [29.81 37.80 54.20 63.32] [54.09 63.28 76.91 85.99] [76.91 85.99 99.61 108.70]

However, users do not need to engage in this calculation since anfisedit GUI produces all output results.

Fig. 9 shows the accuracy of applying the proposed method on the intersection of E 2nd St and Kirman Ave in Reno, NV. Fig. 9(a) illustrates MAPE of regression and ANFIS for both training and test data sets during different conditions. The training data is a data set from which models are built and test data is used to validate the models. The dash line demonstrates regression and the bold line shows ANFIS results. In almost all conditions, ANFIS produces better results. Two extreme conditions are at major streets during low volume hours. While regression produces 53.8% and 55.7% MAPE for training and test data respectively, ANFIS MAPEs are 7.6% and 7.4%. This shows that when there are enough training sets, ANFIS can learn the hidden patterns of data and produce much better models compared to regression. As it was expected, during peak hours errors are lower than other hours and decrease to less than 15%. Fig.

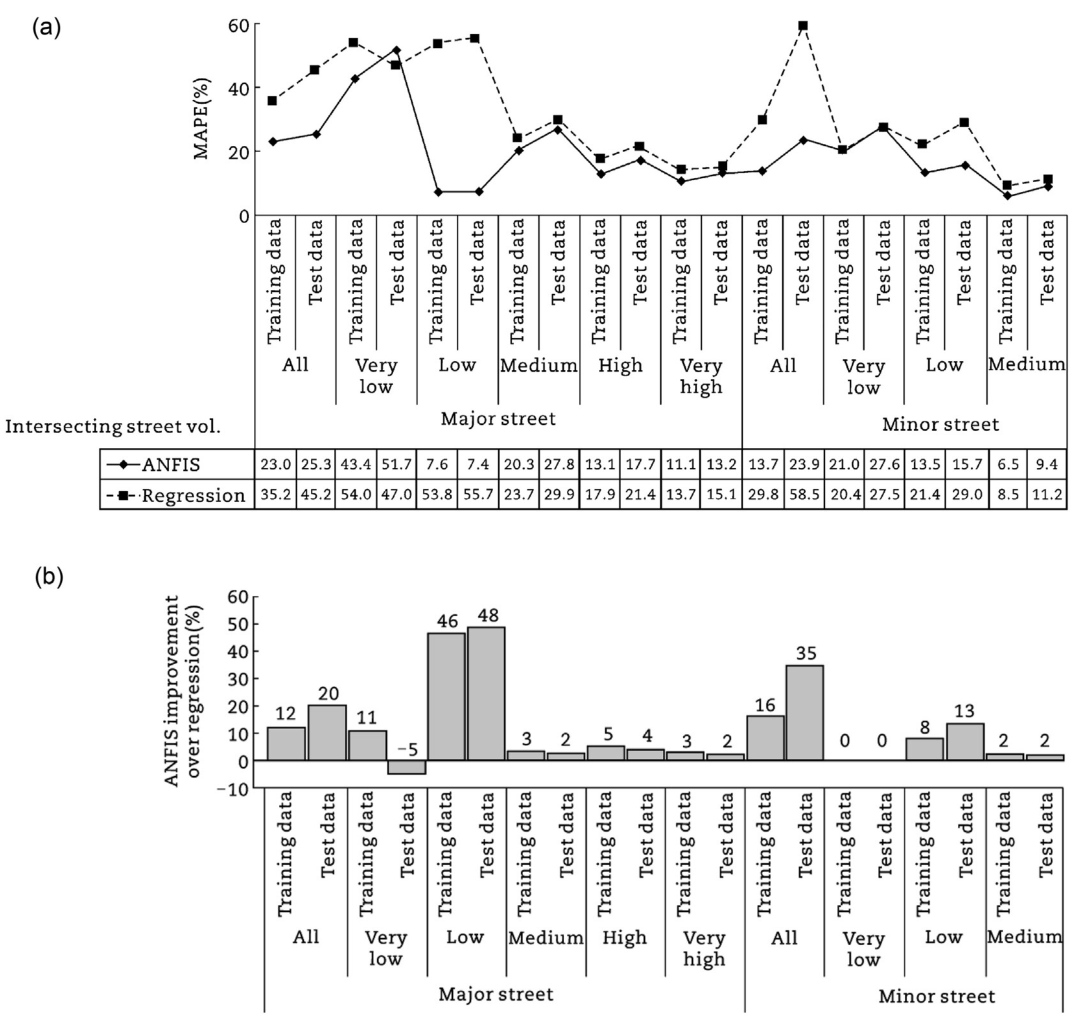


Fig. 9 – Results of intersection of E 2nd St and Kirman Ave, Reno, NV. (a) MAPE of regression and ANFIS for different volume levels. (b) ANFIS improvements over regression for different volume levels.

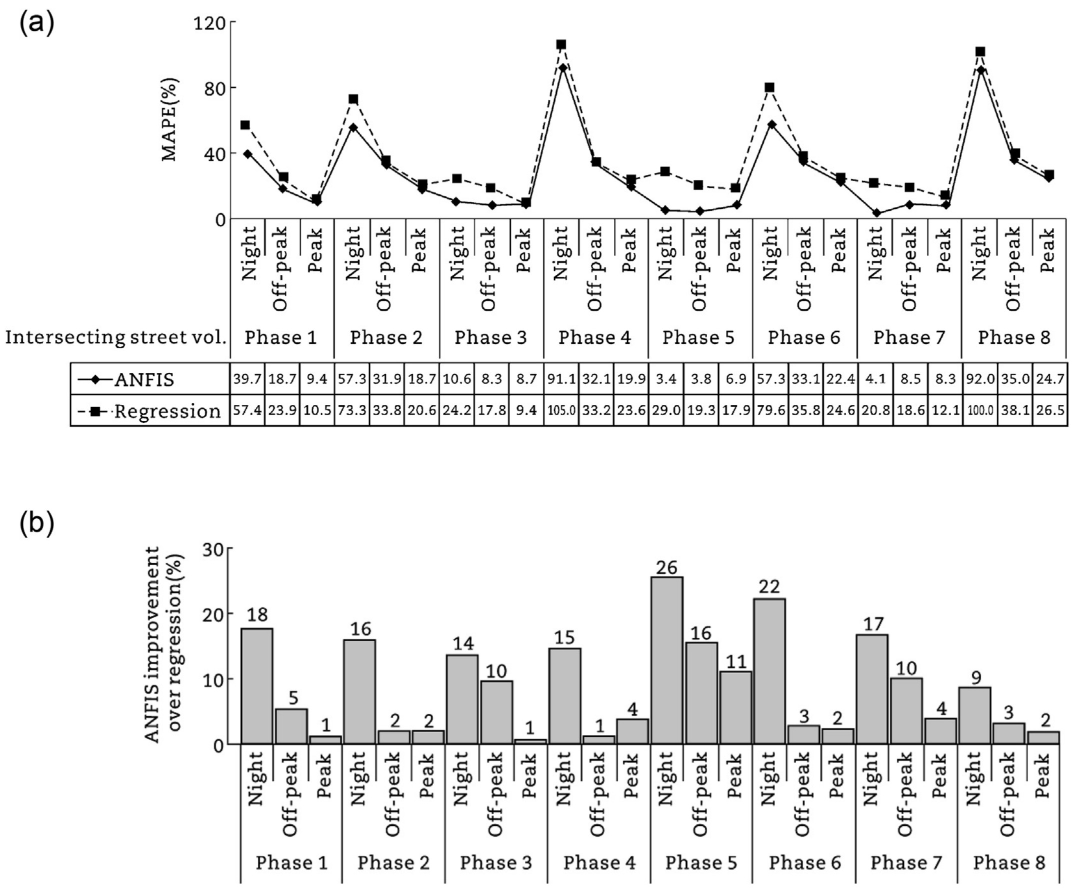


Fig. 10 — Results of intersection of McCarran Blvd and N Virginia St, Reno, NV. (a) MAPE of both ANFIS and regression for different times. (b) ANFIS improvement over regression for different times.

9(b) shows ANFIS improvements over regression. As it can be seen, ANFIS produces better results of up to 48% compared to regression.

Fig. 10 contains similar diagrams for the intersection of McCarran Blvd and N Virginia St in Reno, NV. Here, models were built for eight phases. Time intervals (i.e., intersecting street volume replacement) were categorized into night, off-peak, and peak hours. Because both streets are major streets, during night hours errors are extremely high. This is because green times are not based on volume. However, by increasing the volume during off-peak and peak hours, the accuracy of models also increases. ANFIS produces the following MAPE for phases 1 − 8 during peak hours: 10%, 19%, 9%, 20%, 7%, 22%, 8%, and 25%. Therefore, phases 1, 3, 5, and 7 have errors less than 10% while phases 2, 4, 6, and 8 have errors close to 20%. This means all left turn phases have almost half the error compared to through phases. The reason for this is the fact that left-turn green times are based on gap out. That means they are highly related to volume. Similar to Figs. 9 and 10 also shows that this method is not accurate during off-peak hours. The second diagram of this figure also shows the improvement of ANFIS over regression that can be more than 25%. ANFIS improvement is more significant during night and off-peak hours. The reason is that during these hours, there are more irregularities in data sets and ANFIS is able to learn and consider them.

7. Summary and conclusion

Current detectors in Nevada produce unreliable counts. In this study, a method is proposed to estimate turning volumes from signal information without using detector data. In this method, at first a simulation model is built in VISSIM with different volume inputs. Then, based on this simulation a data set is produced which contains green times in each cycle during the simulation period and their corresponding volume. A model is developed for each phase/turning movement based on this data set and if errors of these models are acceptable, they can be used for future count estimation. For modeling, regression and ANFIS are used. Results show that during peak hours there is a high correlation between actuated green time and volumes at the major street. Minor street green terminates after gap out, or maximum green. Therefore, it is feasible to estimate volume from prediction models at all times. From the results, it can be also concluded that when there are enough records for modeling, ANFIS produces more accurate models compared to regression. MATLAB has a built-in toolbox for ANFIS that facilitates utilization of this powerful modeling method.

The method proposed in this paper does not need extensive data collection and due to VISSIM's detailed outputs and capabilities, it is easy to be employed. Also, there is no need to install new equipment or change and modify existing facilities.

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