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Annual Average Daily Traffic estimation from Seasonal Traffic Counts

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Abstract

This paper presents an approach to estimation of the Annual Average Daily Traffic (AADT) from a one-week seasonal traffic count (STC) of a road section, with the aim of improving the interpretability of results with measures of non-specificity and discord. The proposed method uses fuzzy set theory to represent the fuzzy boundaries of road groups and measures of uncertainty. Neural networks are used to assign a road segment to one or more predefined road groups. The approach was tested with data obtained in the Province of Venice, Italy, for the period of the year in which STCs are taken. The method was found to produce accurate results.

Keywords: AADT Estimate; Artificial Neural Networks; Discord; Non-Specificity

1. Introduction

Information on Annual Average Daily Traffic (AADT) is essential for such diverse fields as pavement design, fuel-tax revenue projections, and highway planning. Monitoring is necessary for accurate AADT estimates, but it is expensive for responsible transportation agencies in terms of costs and personnel.

The Federal Highway Administration Traffic Monitoring Guide (FHWA, 2001) provides transportation agencies with recommendations concerning the design of efficient monitoring programs, based on a combination of portable counters used for a few days (Short Period Traffic Counts, or SPTCs) or at least one week (Seasonal Traffic Counts, or STCs) per year, and Automatic Traffic Recorders (ATRs) which give Permanent Traffic Counts (PTCs). The AADT for a given road section is estimated according to the following steps. First, road groups are determined, according to data collected by ATRs (PTCs); second, the traffic volume of the road section in question is counted for a short period (SPTCs or STCs); third, the road group to which the road section

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in question is similar in terms of traffic flow patterns is identified; and fourth, AADT is estimated by adjusting the SPTC (or STC) volume by an appropriate seasonal adjustment factor for the road group.

The FHWA procedure for estimating AADT has been extensively studied and some critical aspects have been noted, including the definition of road groups, the assignment of a road section to a road group according to short counts, and the importance of missing counts. Gecchele et al. (2012) recently introduced fuzzy set theory to represent the fuzzy boundaries of road groups and measures of uncertainty (non-specificity and discord) to solve the problem of identifying the group which matches the given road section. In their paper, the approach was tested considering passenger vehicle traffic patterns as measured by SPTCs, and results were found satisfactory compared to previous studies. The present paper extends analysis of the predictive capability of the approach, presenting results obtained from one-week traffic counts, which are commonly adopted by transportation agencies as Seasonal Traffic Counts. The original structure of the approach was modified. Analysis was carried out with traffic data from fifty Automatic Traffic Recorder (ATR) sites of the monitoring program of Province of Venice, Italy. The "leave-one-out" approach has been applied to sample traffic data, thus properly simulating the estimation process as it happens in practice.

The paper is organized as follows. Section 2 reviews the literature on the subject. Section 3 briefly describes the FHWA procedure, and Section 4 presents the proposed approach. Section 5 demonstrates a case study, the main results of which are described and discussed in Section 6. Concluding remarks are presented in Section 7.

2. Review of past works and problems

According to past studies on the estimation of AADT, the application of the FHWA procedure may be affected by three sources of error (Bodle, 1967):

1. Error due to day-to-day variations in traffic volumes;
2. Error in grouping road segments (ATR sites) into significant road groups;
3. Error in assigning the road segment along which SPTCS or STCs were obtained to the right road group.

Sampling error: traffic volumes continually fluctuate over time, and any kind of estimation in the transportation field must deal with this common problem.

Error in grouping of road segments: the FHWA suggests three ways of determining road groups according to permanent counts obtained at ATR sites: clustering analysis, geographical/functional classification, and "same road" application of adjustment factors. Each approach has some drawbacks, and analysts choose the "best" method depending on their knowledge of the road network and the availability of traffic data.

Clustering analysis is probably the most commonly applied analytical approach, although results are not considered reliable in some cases. In particular, it has been observed that:

- clusters may change over time; that is, an ATR site may belong to several groups over the years [(Ritchie, 1986); (Faghri, Glaubitz, & Parameswaran, 1996)];
- road groups formed according to clustering cannot have a clear linguistic definition in terms of geographical or functional characteristics, in view of the purely mathematical nature of the process (FHWA, 2001);
- it is often difficult to establish the "optimal" number of road groups (FHWA, 2001).

Various methods have been proposed to solve these problems, including Regression Analysis (Faghri & Hua, 1995), Genetic Algorithms (Lingras, 2001), Artificial Neural Networks (ANNs) [(Faghri & Hua, 1995); (Lingras, 1995)] and a large number of clustering methods, differing from the least-squared minimum distance algorithm proposed by TMG. Some of them were implemented and compared by Gecchele et al. (2011), including agglomerative hierarchical clustering (Ward's Minimum-Variance method (Sharma & Werner, 1981), average linkage method and centroid linkage method (Faghri & Hua, 1995)), partitioning (k-means (Flaherty, 1993)) and model-based clustering (Zhao, Li, & Chow, 2004).

In practice, the results obtained show that an ATR site may belong to more than one road group and that the groups cannot easily be defined in language (e.g. commuter road, recreational road). Gecchele et al. (2012)

applied fuzzy set theory to represent fuzzy boundaries of road groups and to define them in semantic way. In particular they introduced "Don't Know" categories to deal with the situation in which a road section whose AADT has to be estimated appears belong to more than one road group at different degrees of similarity.

Error in assignment of road segments: past studies [(Gulati, 1995); (Davis, 1996)] noted that assigning a road section to the wrong road group can lead to large errors in the estimated AADT.

To guarantee correct assignments and to minimize the risk of large errors [(Davis & Guan, 1996); (Davis, 1997)], the TMG suggests STCs at different periods of the year. Other authors have suggested alternative approaches, including Artificial Neural Networks with SPTCs as input data [(Sharma et al., 1999); (Sharma et al., 2000); (Sharma et al., 2001)] or multiple linear regression [(Seaver, Chatterjee, & Seaver, 2000); (Li, Zhao, & Wu, 2004)] and fuzzy decision trees (Li, Zhao, & Chow, 2006) with socio-economic and demographic data. More recently, Linear Discriminant Analysis (Tsapakis et al., 2011) has been adopted to determine the group assignment of sites monitored with 24-hour SPTCs, in view of the fact that transportation agencies wish to reduce monitoring costs by using the shortest possible traffic counts.

3. The FHWA procedure

With clustering analysis to identify road groups, the FHWA procedure consists of four steps:

Step 1: Grouping ATR (Automatic Traffic Recorder) sites with similar temporal traffic volume variations;

Step 2: Determining average seasonal adjustment factors for each road group;

Step 3: Assigning the road section, monitored with a SPTC (or STC), to one of the groups defined in step 1;

Step 4: Applying to the SPTC (or STC) the appropriate seasonal adjustment factor of the road group, in order to produce the AADT estimate for the road section in question.

According to weekly and monthly variations in traffic volumes, the seasonal adjustment factor for an ATR site k for the i-th day of the week of the j-th month is calculated by:

$$f_{ijk} = \frac{AADT_k}{ADT_{ijk}} \tag{1}$$

where $AADT_k$ is the AADT for the k-th ATR site, ADT_{ijk} is the average daily traffic recorded on the i-th day of the week of the j-th month in the k-th ATR site. The AADT and ADT are generally calculated according to the AASHTO method (AASHTO, 1992). ATR sites are grouped by one of the clustering methods according to the reciprocal of seasonal adjustment factor rf_{ijk}, defined as:

$$rf_{ijk} = \frac{1}{f_{ijk}} \tag{2}$$

Since ATR sites grouped together are presumed to have similar traffic patterns, the seasonal adjustment factors which correspond to (i,j) combinations are calculated for each road group. If n ATR sites are in road group c, the seasonal adjustment factor for the i-th day of the week of the j-th month is calculated by:

$$f_{ijc} = \frac{1}{n}\sum_{k=1}^{n}\frac{AADT_k}{ADT_{ijk}} = \frac{1}{n}\sum_{k=1}^{n} f_{ijk} \tag{3}$$

where $AADT_k$ and ADT_{ijk} for the k-th ATR site in group c are the same as in Eq. 1.

Once a road section is assigned to a group c, the AADT can be estimated by multiplying daily traffic count DT_{ij} obtained for the i-th day of the week of the j-th month by the corresponding seasonal adjustment factor f_{ijc}:

$$AADT_{Estimate} = DT_{ij} f_{ijc} \tag{4}$$

If several one-day counts are available, DT is the corresponding 24-hour average traffic volume. Alternatively, the AADT estimate can be obtained as the average of AADT estimates calculated for each day of counting.

4. Proposed approach

The approach proposed here (Gecchele et al., 2012) preserves the framework of the FHWA procedure and allows analysts to deal with a situation in which a road segment appears to belong to more than one group and to provide the degree of belonging to each group. As shown in Figure 1, the procedure consists of four steps:

1. Grouping ATR sites with the Fuzzy C-means algorithm, based on the seasonal adjustment factors of individual ATRs (see section 1 of Figure 1);
2. Assigning the road segment for which STCs are available to one or more predefined road groups, with neural networks (see section 2 of Figure 1);
3. Calculating the measures of uncertainty associated with the assignment to road groups (see section 3 of Figure 1);
4. Estimating AADT as the weighted average of STC volumes, adjusted by the seasonal adjustment factor of the assigned road group(s) (see section 4 of Figure 1).

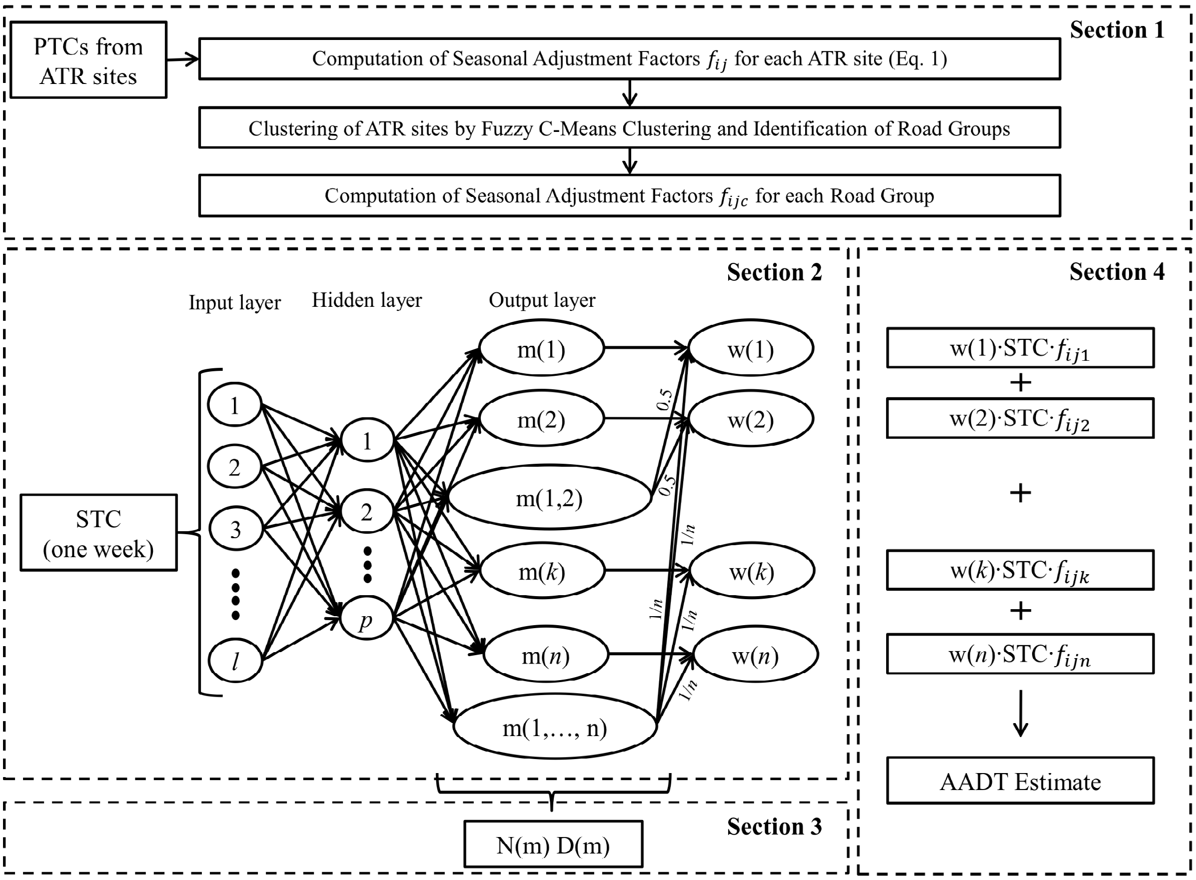

Fig. 1. Scheme of proposed approach (adapted from Gecchele et al., 2012)

The steps are briefly explained below (for further details, see Gecchele et al., 2012). As observed in Section 1, the objective of this paper is extending investigation of the predictive capability of the original approach, by analyzing AADT estimates obtained from one-week STCs. According to the differences existing between SPTC and STC data structures, sections 2 and 4 (assignment and AADT estimation) were modified from the original procedure.

4.1. Grouping Step

An ATR site *i* may belong to more than one group, with different degrees, ranging between 0 and 1 (fuzzy boundaries), where 0 indicates no belonging to a group, and 1 represents complete belonging to a group. Given the number of groups C, the Fuzzy C-means algorithm (Bezdek, Ehrlich & Full, 1984) provides the degree to which an ATR site belongs to each group, assuming fuzzy group boundaries.

4.2. Assignment Step

The proposed approach adopts a multi-layered, feed-forward, back-propagation neural network to assign the input, i.e., the given STC traffic pattern, to the output, represented by the road group(s) which matches the pattern (for further details of the neural network structure, see section 5.3.2).

4.3. Measures of uncertainty in assignments

The assignment of a road section to a road group is affected by uncertainty, which is investigated with two measures developed in Dempster-Shafer theory (Klir & Wierman, 1999), Non-Specificity and Discord, for which expressions are provided. These measures are used to characterize the traffic pattern data (STC) collected at the road section, which is to be classified to one or more predefined road groups.

Consider that the output nodes of the neural network represent all possible combinations of road groups (2^n), given by the power set of road groups 1 to n (e.g. (1 or 2), (1 or 2 or 3)). Consider also that the weight associated with each final node is the degree to which the traffic pattern supports individual power sets of road groups.

Let the weights associated with final node be shown by *m(x)*, where *x* is a road group or more than one road group, and $\sum m(x)=1$. When *m(A)*=1, the road section in question certainly belongs to road group A. When *m(A or B)*=1, the road section in question belongs to either A or B, but exactly which is uncertain. When *m(X)*=1, where *X* is all road groups, the road section in question may belong to any of the groups, which is the “Don’t know” situation. Given the probability distribution *m(x)*, the measure of non-specificity *N(m)* and the measure of conflict *D(m)* are developed.

N(m) provides the measure of uncertainty in that the available traffic pattern has no specific information about which road group the road section belongs to. It can be calculated by:

$$N(m)=\sum_{A\in F} m(A)\cdot \log_2 |A| \tag{5}$$

where $|A|$ is the number of road groups in power set A. The value of $N(m)$ is within $[0, \log_2|X|]$. X is the universal set (all road groups) and $|X|$ is the number of these groups. The minimum of $N(m)$ is obtained when $m(A)=1$, or the probability of belonging to a particular road group is 1. The maximum of $N(m)$ corresponds to the case of “Not able to assign to any specific group”.

$D(m)$ provides the measure of uncertainty, in that the available traffic pattern contains conflicting information, i.e., a certain pattern at a particular time points to one group and at other times to another. It can be calculated by:

$$D(m) = -\sum_{A \in F} m(A) \log_2 \left(\sum_{B \in F} m(B) \frac{|A \cap B|}{|B|} \right) \quad (6)$$

where $|B|$ and $|A \cap B|$ are the numbers of power sets associated with group B and for intersections among subsets A and B, respectively.

4.4. Estimating AADT

Estimation of AADT from the available STC is made by considering the degree to which a road section belongs to each group, which is found in the output of the neural networks, and the values of each daily traffic volume DT_m, where m indicates the m-th monitoring day of the week ($m = 1,\ldots,7$). AADT estimates are calculated for each day of the week, and the final value for the entire week is obtained by averaging these values. However the analyst can choose other estimates depending on his/her preferences (e.g. estimate from Wednesday data or average of weekdays only).

For example, if the degrees of belonging to road group 1 and (1 or 2) are $m(1)$=0.4 and $m(1,2)$=0.6, respectively, the final weights adopted for the estimate are calculated as $w(1)$=0.4+0.6/2=0.7 and $w(2)$=0.6/2=0.3. Therefore $AADT_m$, the AADT estimate for a given day m (e.g. m = 1, that is, Monday) is calculated by:

$$AADT_m = w(1) \cdot DT_m \cdot f_{ij1} + w(2) \cdot DT_m \cdot f_{ij2} = 0.7 \cdot DT_m \cdot f_{ij1} + 0.3 \cdot DT_m \cdot f_{ij2} \quad (7)$$

where f_{ij1} and f_{ij2} are found in Eq. 3.

Then, if the entire week is considered (7 monitoring days), the final AADT estimate is given by Eq. 8:

$$Final\ AADT = \frac{\sum_{m=1}^{7} AADT_m}{7} \quad (8)$$

5. Case study

The proposed approach was implemented in a real-world situation in Italy. According to traffic data recorded by ATRs in the road network, road groups were established with the Fuzzy C-means algorithm. A large number of STCs were extracted from each ATR site, and AADT was estimated from each STC and compared with the actual AADT of the ATR site, to test the validity of the approach.

5.1. Data used

The traffic data used in this study were obtained for the year 2005 at 50 ATR sites on the rural road network of the Province of Venice (Della Lucia, 2000). Each ATR monitors the two-lane road section, recording hourly directional traffic volumes on a single lane and describing temporal traffic patterns in great detail [(Tsapakis et al., 2011); (Gecchele et al., 2011)].

Volume data are divided into two classes, passenger vehicles and trucks, with reference to a 5-m length threshold. This case study focuses on estimating AADT for passenger vehicles only, because traffic patterns for trucks were found to differ from those of passenger vehicles (FHWA, 2001) and must therefore be considered separately (Rossi et al., 2012).

5.2. Data treatment

The total amount of available hourly volumes of each ATR site was sampled to form STCs one week long (168 hours), yielding 1525 STCs. Analysis was carried out according to the "leave-one-out" approach (Witten & Frank, 2005):

1. An ATR site was selected as a validation site and sample STCs from that site became the validation dataset;
2. STC data from the remaining ATR sites were used as the calibration dataset to train the ANN;
3. Each STC of the validation site was assigned to road group(s) by trained ANN and AADT was estimated.
4. The process was repeated, each ATR site at a time being used as a validation site, thus generating a large number of samples and AADT estimates.

5.3. Model implementation

Three tasks are conducted to implement the proposed model: establishing road groups, developing and executing artificial neural networks, and calculating AADT. The details reported here for the first task are those presented in Gecchele et al. (2012), since the input data are the same.

5.3.1. Establishing road groups with Fuzzy C-Means algorithm

Traffic data for passenger vehicles from the 50 ATR sites were used to establish road groups. Eighteen seasonal adjustment factors were used to describe seasonal variations in traffic flow at each site, according to the combination of 3 types of day (Weekdays, Saturdays, Sundays) and six two-month periods (period 1 = January-February, 2 = March-April, 3 = May-June, 4 = July-August, 5 = September-October, 6 = November-December). This choice reflects the structure of the monitoring program currently used by the Province of Venice.

Implementation of the Fuzzy C-means algorithm requires the number of groups (C) to be specified in advance. Since the appropriate number was not known a priori, the algorithm was tested by changing the values of C from 2 to 20. The best number of groups was chosen by comparing the values of the Dunn Index (Dunn, 1974), Silhouette measure (Rousseeuw, 1987), Pseudo F Statistic (Calinski & Harabasz, 1974) and G2 index (Goodman & Kruskal, 1954). The robustness of the solution was also tested by running the algorithm for different time periods, changing the starting point and verifying the stability of results.

Values close to 1 for Dunn Index, Silhouette measure and G2 index indicate well separate clusters, which maximize the similarity among observations belonging to the same group (internal cohesion) and minimize the similarities with observations in other groups (external separation). Similarly, the Pseudo F Statistic analyses the hierarchy at each level and reveals the optimal number of clusters for peak values.

Figure 2 shows the values of the indices (average values of results) plotted against the number of road groups. Peak values of indices (maximum) are observed for three and eight road groups. Eight road groups were chosen as the "optimal" number of groups, because they can represent traffic patterns variability with greatest details.

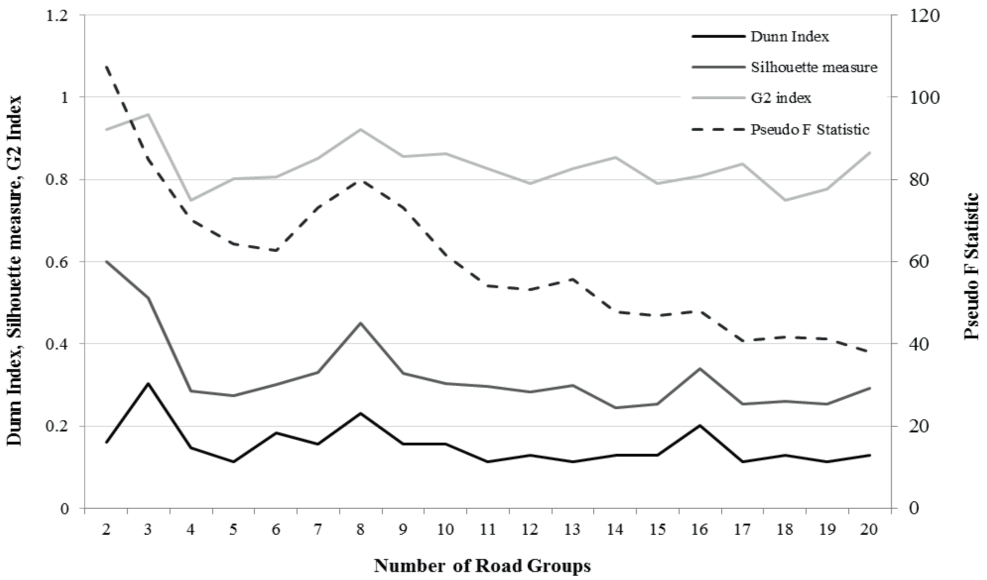

Fig. 2. Clustering indices plotted against the number of road groups

Once the number of groups was fixed at 8, the belonging of each ATR to a road group was checked by analysing the highest membership grade. The results clearly show that the ATR belongs to a road group or a "Don't know" situation (see Hanesh, Sholger, & Dekkers, 2001 and Gecchele et al., 2012 for details). Three "Don't know" cases were identified: Group "1 or 3 or 4" with 4 ATRs, Group "1 or 2 or 3" and Group "1 or 3" with 2 ATRs each.

Figure 2 shows the average reciprocals of seasonal adjustment factors rf_{ijk} (Eq. 2) for different days and periods of the year, plotted for each well-defined group. Road groups obtained from clustering clearly indicate the existence of varying traffic patterns. Groups 1 (8 ATRs), 2 (6 ATRs), and 3 (10 ATRs) may be characterized as commuter roads, having stable traffic patterns during the year, with peaks during weekdays and decreased traffic on Sundays. Groups 5 (4 ATRs), 6 (4 ATRs), 7 (2 ATRs) and 8 (2 ATRs) are "recreational" roads, with lower volumes in winter and peaks in summer, particularly during week-ends. Group 4 includes 6 ATRs with intermediate characteristics.

Figure 4 shows the ATR sites location in the road network and the road groups they belong to. As can be observed in Figure 4, ATRs were grouped following clear spatial patterns, which explain observed temporal traffic patterns. ATRs belonging to commuter road groups (1, 2, 3) are located in the inland parts of the province, where tourist activities are limited and traffic patterns are supposed to be quite stable during the year. ATRs belonging to recreational road groups (5, 6, 7, 8) are located in the coastal part of the Province of Venice (groups

7 and 8) or on roads which give access to tourist facilities (groups 5 and 6). This means that in summer period these roads are supposed to be characterized by very high passenger car volumes compared to winter period. ATRs belonging to road group 4 are representative of intermediate characteristics between commuter and recreational roads. Their location in the road network (between the inland and the coastal line) confirms these characteristics. ATRs classified as ”I don’t know cases”, which are mainly characterized by commuter-type patterns, are in the inland parts of the Province.

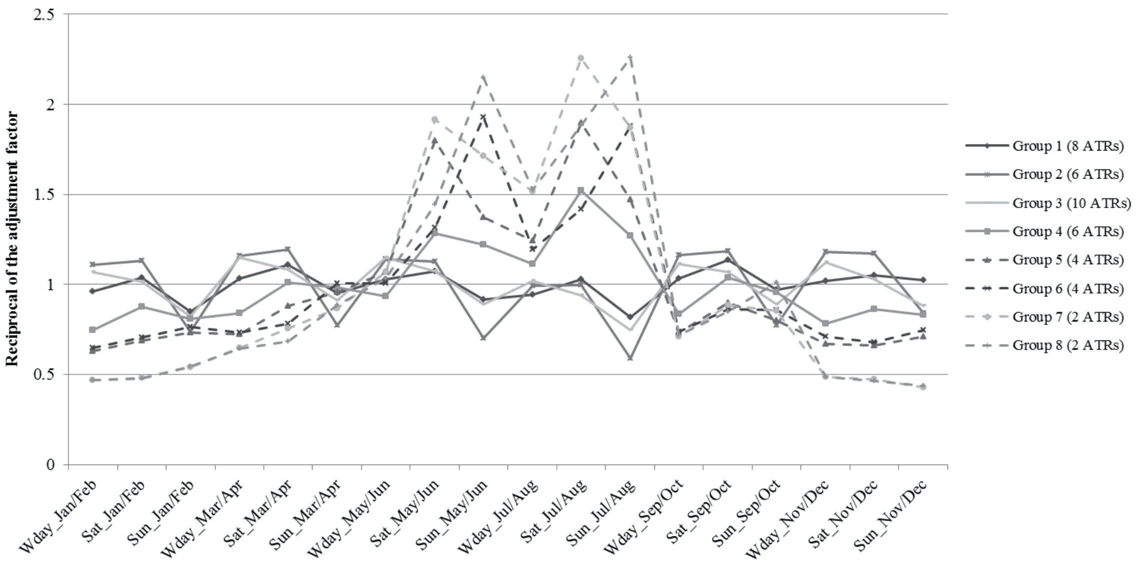

Fig. 3. Combinations of day-type and two-month period vs. average reciprocals of the seasonal adjustment factors rf_{ij} for road groups

5.3.2. Developing Artificial Neural Networks

Multi-layered, feed-forward, back-propagation, artificial neural networks (ANNs) were developed to assign the STCs to the road groups. Training and testing datasets provided to the ANN in the input layer had the same structure and included information available from the STCs.

Therefore the input layer includes 176 input nodes: one node describing the two-month period of the year, 168 nodes for hourly factors h_l, and 7 nodes for daily factors d_l.

The hourly factor, h_l, was defined by:

$$h_l = \frac{HT_l}{WT} \tag{9}$$

where $l = 0,\dots,168$ was the starting time for the hourly count in the week (24 hours by 7 days), HT_l was the hourly traffic volume for hour l and WT the weekly volume for the specific STC. Similarly, daily factor d_l was the ratio between daily traffic DT and weekly traffic WT (7 d_l factors for 7 days).

The output layer had 11 nodes, one node for each road group identified in the clustering step (including “Don’t know” cases). This choice was done with the aim of properly training the ANNs and reducing the complexity of the assignment problem. In the hidden layer the number of nodes was equal to 90 nodes, following the *rule of thumb* which assigns to the hidden layer half of the sum of input and output nodes.

5.3.3. Calculation of AADT

In this step, each STC in the test dataset was assigned by the corresponding ANN, obtaining the probabilities of belonging to each road group. The STC volume was used to estimate the AADT, following Eqs. 7 and 8.

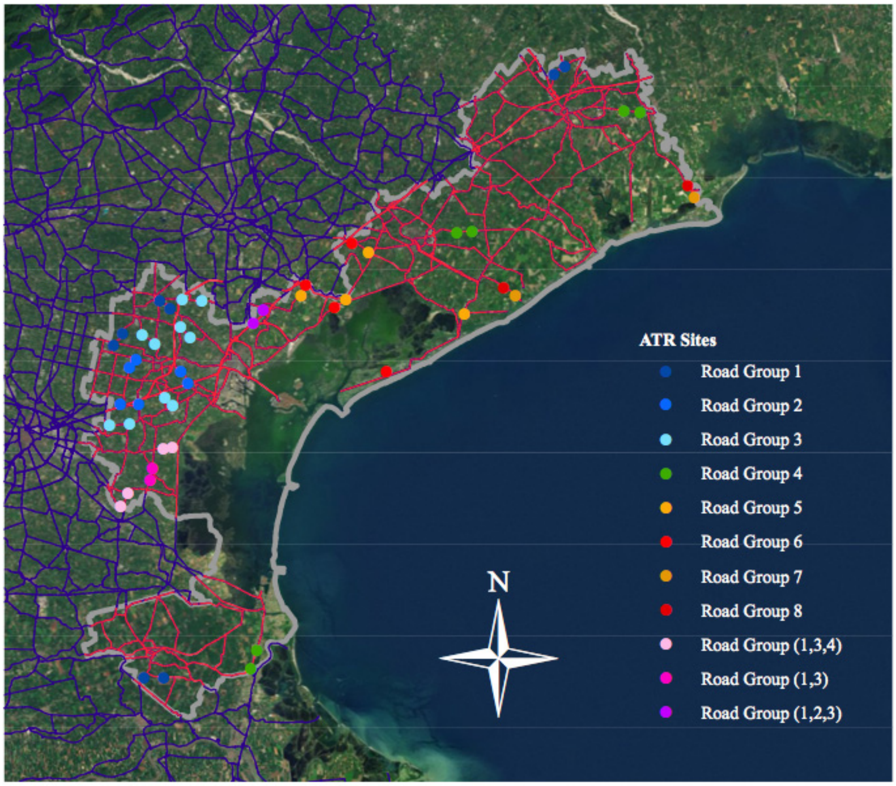

Fig. 4. Location of ATR sites in the rural road network

6. Results and Discussion

6.1. Examination of estimated AADT

The goodness of estimates was evaluated by comparing the actual AADT for an ATR site with the estimated AADT from each STC for the same site. For each STC, the percent absolute estimation error was calculated:

$$\Delta = \left| \frac{AADT_{estimate} - AADT_{Actual}}{AADT_{Actual}} \right| \times 100 \tag{10}$$

The Mean Absolute Percent Error (MAPE) and the Standard Deviation of Absolute Percent Error (SDAPE) were used to analyse the accuracy of the resulting AADT estimates. Table 1 shows details of the MAPE and

SDAPE values for different tests: by group, different day-types (weekdays, Saturdays, Sundays, entire week) and period of the year.

Table 1. MAPE and SDAPE values obtained from STCs by group, day-types and period of the year

Group	Day	Period					
		Jan-Feb	Mar-Apr	May-Jun	Jul-Aug	Sep-Oct	Nov-Dec
1	1	7.74 (8.35)	7.95 (8.09)	4.67 (2.99)	8.69 (10.21)	6.43 (6.08)	18.48 (17.15)
	2	11.58 (10.45)	8.81 (7.50)	5.94 (4.33)	11.48 (11.11)	7.73 (5.91)	26.29 (18.27)
	3	8.92 (7.15)	9.55 (7.33)	8.43 (5.56)	18.69 (15.03)	7.88 (5.13)	24.05 (24.69)
	Week	7.92 (8.11)	7.63 (7.35)	4.47 (2.98)	9.46 (10.99)	5.78 (5.73)	20.01 (18.26)
2	1	15.01 (12.4)	7.81 (3.47)	4.45 (3.28)	10.76 (10.22)	8.2 (8.52)	28.27 (24.79)
	2	16.45 (13.36)	6.88 (6.67)	7.25 (5.18)	15.55 (12.20)	8.41 (7.24)	37.23 (32.99)
	3	9.82 (5.59)	17.91 (8.10)	25.91 (7.89)	32.49 (11.66)	14.27 (6.93)	20.07 (21.48)
	Week	11.87 (10.74)	4.06 (2.87)	7.2 (3.62)	13.96 (10.70)	5.88 (6.82)	26.94 (25.81)
3	1	7.27 (9.42)	6.03 (7.11)	4.44 (3.07)	10.43 (11.37)	6.77 (9.75)	13.19 (19.16)
	2	7.89 (7.09)	5.93 (5.13)	8.81 (5.59)	19.09 (12.93)	9.15 (5.82)	14.79 (20.04)
	3	8.83 (6.44)	6.58 (5.44)	11.98 (8.46)	20.04 (16.74)	6.94 (4.43)	12.07 (15.98)
	Week	6.47 (8.13)	5.21 (5.57)	5.56 (3.32)	12.22 (12.44)	6.4 (7.67)	12.86 (18.74)
4	1	28.13 (11.17)	10.54 (5.00)	5.59 (3.47)	9.19 (8.08)	16.5 (8.82)	23.33 (13.37)
	2	44.69 (18.97)	23.3 (13.81)	11.51 (8.06)	19.42 (19.84)	20.16 (11.49)	43.95 (20.55)
	3	37.47 (24.39)	17.54 (11.55)	15.34 (10.95)	19.46 (8.62)	19.71 (14.95)	37.15 (26.23)
	Week	31.83 (13.51)	12.37 (6.16)	6.95 (3.83)	11.22 (9.25)	17.29 (9.50)	28.25 (15.75)
5	1	5.68 (3.63)	9.02 (6.75)	12.12 (7.73)	18.67 (19.66)	11.88 (10.02)	10.51 (12.13)
	2	7.31 (3.68)	14.22 (13.05)	19.78 (15.12)	18.04 (15.11)	17.21 (6.28)	12.96 (15.20)
	3	11.61 (7.81)	15.44 (7.82)	13.96 (9.38)	21.82 (11.64)	11.47 (9.78)	16.18 (5.98)
	Week	4.83 (3.82)	8.54 (8.40)	11.54 (7.58)	17.35 (17.33)	12 (7.86)	11.4 (11.15)
6	1	9.14 (10.00)	9.76 (7.66)	10.98 (9.26)	17.03 (13.05)	18.39	21.36 (6.41)
	2	13.4 (15.92)	11.26 (9.41)	17.5 (7.53)	17.18 (9.85)	17.87	28.8 (14.27)
	3	10.28 (5.58)	13.08 (9.83)	33.93 (16.73)	54.82 (49.38)	13.05	22.96 (16.75)
	Week	9.04 (9.58)	8.34 (5.71)	12.85 (9.71)	22.2 (15.72)	17.56	22.65 (9.01)
7	1	21.63 (16.28)	18.28 (12.96)	21.33 (16.47)	36.16 (13.04)	27.46 (22.47)	26.67 (23.09)
	2	23.46 (17.10)	22.1 (13.96)	48.36 (32.74)	47.13 (33.73)	29.5 (22.82)	31.12 (19.19)
	3	15.54 (12.33)	15.07 (8.44)	44.39 (33.60)	49.98 (27.17)	27.15 (18.17)	28.42 (20.82)
	Week	20.41 (15.99)	15.65 (12.66)	27.54 (19.64)	39.66 (15.71)	27.25 (20.71)	27.07 (22.45)
8	1	31.84 (13.38)	23.91 (10.86)	16.77 (15.96)	51.95 (23.80)	32.09 (19.04)	35.75 (11.17)
	2	34.82 (13.09)	24.64 (12.86)	29.33 (26.62)	62.73 (27.98)	31.26 (16.72)	38.12 (15.16)
	3	13.62 (11.66)	13.66 (5.86)	73.13 (30.80)	80.71 (53.97)	34.96 (32.27)	31.79 (14.46)
	Week	29.19 (13.20)	20.43 (10.54)	22.91 (20.88)	57.6 (27.02)	30.64 (20.81)	35.52 (11.99)

Note: 1 = Weekdays, 2 = Saturdays, 3 = Sundays, Week = all week included; SDAPE values within brackets

According to Table 1, the following observations may be made:

- AADT estimates based on traffic volumes observed on weekdays (Day = 1) are generally more accurate than those obtained at weekends (Day = 2 or 3). This is explained by noting that weekday traffic patterns are generally stable and may represent "average" traffic conditions better than week-ends;
- AADT estimates based on average daily volumes (Day = Week) make a balance among the estimates obtained from single day volumes, maximizing the information available from the STC;
- Recreational roads (Groups 4-8) have larger MAPE and SDAPE values than those of commuter roads (Groups 1-3). This is due to tourism along the coast of the Province of Venice, which cause such great variations in traffic volumes on the recreational roads of the network that the approach cannot completely forecast and interpret them;
- The distribution of errors is affected by the time of year. Summer (July-August) and winter (November – December) have larger error values than the rest of the year, particularly in spring (March-April and May-

June). Also in this case, more accurate AADT estimates are explained by the lower variability in traffic patterns observed in spring.

According to TMG requirements for AADT estimation errors (less than 10% only for commuter roads), the approach can be adopted to estimate AADT with sufficient accuracy, if due attention is paid to some points at specific moments of the year (summer and winter). This result is of particular interest, because seasonal traffic counts (lasting one week) are commonly adopted by transportation agencies as short counts in monitoring.

However, in the future, this work should be improved by specific analysis of recreational roads, with the aim of further reducing estimation errors. In this sense, additional information on the socio-economic and land-use characteristics of the environment of the road section seems to be promising (Caceres, Romero, & Benitez, 2012).

7. Summary and Conclusions

This work applied a new approach based on one-week seasonal traffic measures to estimate AADT for passenger vehicles. The approach, which maintains the structure of the FHWA method, introduces mechanisms to deal with the vagueness of boundaries between individual road groups, and adopts measures of uncertainty (non-specificity and discord) to solve the problem of identifying which group matches a given road section.

Passenger vehicle traffic data from 50 ATR sites in the road network of the Province of Venice, Italy, were adopted for this analysis, which found that:

- the accuracy of AADT estimates, measured by MAPE and SDAPE, was satisfactory, mainly for commuter roads, according to FHWA requirements;
- the accuracy of the AADT estimates obtained were influenced by the period in which they were taken, which depends on specific land-use and socio-economic characteristics.

In future, this work should be extended to consider the influence of the socio-economic and land-use characteristics of the environment of the road section in question, when identifying road groups and assigning STCs, particularly for recreational roads.

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