AN ANALYSIS OF SEASONALITY AND LONG-TERM TREND OF LOS ANGELES HIGHWAY TRAFFIC VOLUMES

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Abstact: Traffic counts continuously collected at automatic traffic recorder stations are a kind of time series data, a set of sequentially ordered observations in time. Traffic volumes are the representative values of traffic counts. Traffic volumes contain regular and/or irregular error terms such as long-term trend, seasonal variation, or monthly variation. The direct use of observed link volumes may result in irrelevant outcomes in traffic flow analyses. This research applies the decomposition method to measure seasonal and trend variations of Los Angeles highway traffic volumes collected by the California Department of Transportation (Caltrans) from October 1986 to June 1993. The decomposition method consists of two models: an *ad hoc* smoothing model for seasonal and irregular variations and a linear regression model for long-term pattern of traffic volumes. Results demonstrate the applicability of the decomposition method in identifying seasonal and trend indices from time-series link volumes.

1. INTRODUCTION

Link traffic volumes represent the traffic loads on transportation network links. They provide basic information for transportation analyses and forecasting, as well as for facility design, monitoring, and operation. Continuous traffic counts collected at automatic traffic recorder stations are the typical time series data, a set of sequentially ordered observations in time. Traffic volume is the representative value of many traffic counts collected from the same traffic count station given the same time interval. Traffic volumes fluctuate by year (long-term trend), by month of year (seasonal variation), by day of the month (monthly variation), by day of the week (daily variation), by hour of the day (hourly variation), and by minutes of the hour (sub-hourly variation) as well as irregular components and discontinuities.

Highway investment projects, transportation policies, and/or transportation facility disruption due to natural disasters require traffic impact analyses by comparing before- and after-conditions of traffic. However, the direct use of link volumes collected from different months may result in irrelevant outcomes by including error terms such as seasonality or trend. Consequently, the adequate adjustment of dynamic variations of observed link volumes is absolutely critical for the accurate results of traffic impact analyses.

The objective of this research is to develop a procedure for identifying seasonal and trend variations from observed link volumes. This research applies the decomposition method to measure both seasonal and trend variations of Los Angeles highway traffic volumes collected from the California Department of Transportation's (Caltrans') traffic count stations between October 1986 and June 1993. The decomposition method consists of two models: an *ad hoc* smoothing model and a simple linear regression model. The *ad hoc* smoothing model is employed to compute seasonal indices from monthly average daily traffic volumes. The simple linear regression model is used to identify the long-run trends of deseasonalized traffic volumes.

2. LITERATURE REVIEW

There are three broad approaches for addressing the flow pattern changes of observed volumes: (1) the regression approach, (2) the moving average approach, and (3) the mixture of the two approaches.[1] The regression approach contains autoregressive (AR) time series models. Oum (1989) categorizes AR models into the following four groups in terms of functional forms:

(1) linear models,

(2) log-linear models,

(3) logit models, and

(4) translog models.

The moving average approach is classified into two kinds of models: filtering models and smoothing models. Filtering models separate noise by assigning initial parameter values, and by applying parameter adjustment algorithms to iteratively update the values. Smoothing models exclude the residual error values of many periods according to some exponential weighting schemes (Moorthy and Ratcliffe, 1988).

The mixed approach involves autoregressive moving average (ARMA) models and decomposition models. Many stationary random processes have the qualities of both moving average and autoregressive processes (Pindyck and Rubinfeld, 1991). ARMA models use mixed statistical procedures for estimating the autoregressive and moving average coefficients of the observed time series data (Johnson *et al.*, 1987).

[1] Hamed *et al.* (1995) classify the forecasting models of traffic volumes into five groups: Kalman filtering models, prediction error minimization and maximum likelihood models, time-series models, spectral models, and adaptive prediction models.

Decomposition models are based on the idea that time series data can be represented as the product of the four components: trend, seasonality, cyclicality, and random error. The *ad hoc* structure of decomposition models isolates each of the first three components (trend, seasonality, and cyclicality) leaving the residuals in order to make errors as random as possible (Moorthy and Ratcliffe, 1988).

There are five different dynamic patterns of link volumes: subhourly variation, hourly variation, daily variation, seasonality, and trend. Subhourly and hourly variation studies examine the dynamic change of peak hour travel demands. Newell (1967) measured the statistical fluctuations of peak short-time (1-, 5-, or 15-minute) traffic counts by using a stochastical model. Ahmed and Cook (1979) compared an ARIMA model with moving average, double-exponential smoothing, and Trig and Leach adaptive models. Hamed *et al.* (1995) applied the Box-Jenkins auto-regressive integrated moving average (ARIMA) model to analyze a set of 1-minute interval traffic volumes. Vaughan (1970) investigated the distribution of hourly volumes using the exponential-normal model and the mixture of distribution model. Sparks (1976) and Sharma *et al.* (1996) addressed the stochastic properties of peak-period link volumes. Sharma *et al.* (1996) provided a simple procedure for the daily traffic variations.

Seasonality is a cyclical pattern that regularly recurs over a 12-month period. The seasonal index is a measure of how much the value of the variable in a particular period deviates from the average of the variable over the 12-month period (Johnson *et al.*, 1987). Seasonal adjustment is an important process when traffic volumes significantly fluctuate month by month. Strong seasonal fluctuations in link volumes may reflect the dynamic change of social and economic activities of the region (TRB, 1985).

Identifying seasonal variations from observed link volumes has been the subject of interest to traffic engineers. A variety of seasonal adjustment approaches have been introduced and evaluated. Examples include: the application of autoregressive integrated moving average (ARIMA) models (Nihan and Holmesland, 1980), the use of factor grouping methods (Hartgen and Lemmerman, 1983), the applications of factor grouping methods and regression models (Ritchie, 1986), the application of autoregressive moving average (ARMA) models (Moorthy and Ratcliffe, 1988), the application of linear regression models (Sharma and Oh, 1989), the comparison study between eleven regression models and eleven ARIMA models (Vaziri *et al.*, 1990), and research comparing the clustering approach with the regression approach (Faghri and Chakroborty, 1994).

Identifying trends in observed link volumes is another important task. Trends may be linear, growing by a constant absolute amount over time, in exponential form growing by at a constant rate over time, or in a more complicated nonlinear form. The regression analysis approach is the dominant method in trend analysis of link volumes. Johnson *et al.* (1987) and Lardaro (1993) introduced two types of linear trend models using an OLS method: simple regression models and multiple regression models. Kennedy (1992) explained two more sophisticated methods: autoregressive integrated moving average (ARIMA) models and the structural econometric time series approach (SEMTSA).

Granger (1989) classified trend models into six groups in terms of functional forms: the straight line, the exponential curve, the parabolic curve, the modified exponential curve, the Gompertz curve, and the logistic curve forms. Pindyck and Rubinfeld (1991) and Ramanathan (1992) categorized them into six groups: linear trend models, exponential growth models, autoregressive trend models, logarithmic autoregressive trend models, quadratic trend models, and logistic growth models. Faghri and Chakroborty (1994) applied the simple linear regression model to examine the trend of link volumes. Benjamin (1986) introduced logistic models in trend analysis.

3. THE DESCRIPTION OF STUDY AREA

The Los Angeles metropolitan area is the second-largest metropolitan area in Northern America. The Los Angeles metropolitan area consists of five counties: Los Angeles, Orange, Riverside, San Bernardino, and Ventura Counties. The Los Angeles region has around 180 municipalities including the nation's second largest city, Los Angeles. The region has 14.2 million residents and 7.03 million jobs in 1990.

The Los Angeles freeway/roadway system is the backbone of regional mobility, carrying out a huge amount of trips on a daily basis. The existing Los Angeles freeway/roadway system consists of approximately 3,380 miles of federal and state highways, 3,450 miles of major arterials, and massive secondary arterials and local streets. Federal and state highways in the five counties of the Los Angeles region are managed by three districts of Caltrans: Los Angeles and Ventura Counties by District 7, Riverside and San Bernardino Counties by District 8, and Orange County by District 12. Arterials and local streets are managed by city governments.

Trips in the Los Angeles region heavily depend on the use of automobile. The 1991 Southern California Origin-Destination Survey data for the Los Angeles region showed that vehicle trips accounted for approximately 90 percent of all home-work trips and 83 percent of all non-home-work trips. Public transit trips were only around 4.5 percent of all home-work trips and 1.8 percent of all non-home-work trips. The remaining trips consisted of other modes such as walk, bicycle, school bus, motorcycle, taxi/shuttle, or Amtrak. Drive alone vehicle trips accounted for an average of 74 percent of all home-work trips and 39 percent of all non-home-work trips.

The Los Angeles freeway system is the principal facility for both regional and local automobile trips. The freeway system comprises only 15 percent of the total freeway/roadway system mileage. However, the freeway system carries slightly more than 50 percent of total vehicle miles traveled (VMT) within the Los Angeles region. The freeway system includes approximately 1,100 centerline miles of a high-occupancy vehicle (HOV) network for carpools, vanpools, and express buses. The freeway system also includes 14.5 miles of the Santa Monica Freeway Smart Corridor and 10 miles of two toll lanes in each direction within the median of State Route 91.

This research investigates the area of Caltrans District 7 because the Los Angeles County is the core of the Los Angeles metropolitan area. The area of Caltrans District 7 includes over 8.4 million population, 26 freeways, 597 freeway miles, 790 traffic count stations, and over 6 million registered vehicles. The highways of Caltrans District 7 serve 81 million vehicle miles daily, 1 million vehicle trips during morning rush hours (6-9 AM), and 1.5 million vehicle trips during evening rush hours (3-6 PM). Each person makes an average of 3.5 trips daily. Around 62 percent of total trips and 60 percent of vehicle driver trips in the Los Angeles region occurred in the Los Angeles and Ventura Counties (SCAG, 1993).

4. A METHOD FOR EXTRACTING SEASONAL AND TREND VARIATIONS

Traffic volumes contain trend, seasonality, outliers, irregular components, and discontinuities. A variety of analytical methods are developed in identifying seasonal and trend variations of observed traffic volumes. The seasonality study identifies a cyclical pattern that regularly recurs over a 12-month period. Seasonality provides information about regularity in the series that can aid in making a forecast. The trend of traffic volumes is a long-term traffic pattern. The trend can be a linear, an exponential, or a more complicated nonlinear form.

This research applies the decomposition method to address the seasonal and trend patterns of traffic volumes. The decomposition method is the *ad hoc* method based on the idea that the variations of a time series link volume can be represented as the product of the following four components (Pindyck and Rubinfeld, 1991):

$$y_t = L \times S \times C \times I \tag{1}$$

where

y_t = *directed time series traffic volume,*
L = *value of the long-term secular trend in series,*
S = *value of seasonal component,*
C = *(long-term) cyclical component, and*
I = *irregular component.*

The decomposition method isolates each of the components, and attempts to measure both the seasonal and the trend variations in the series.

An *ad hoc* smoothing model is used to remove the combined seasonal and irregular components $S \times I$ from the original series y_t. The smoothing model computes the 12-month average $y_t^{\sim}$ as an estimate of $L \times C$:

$$y_t^{\sim} = \frac{1}{12}(y_{t+6} + \ldots + y_t + y_{t-1} + \ldots + y_{t-5}) \tag{2}$$

The value $y_t^{\sim}$ is relatively free of seasonal and irregular fluctuations.

The original data is now divided by the 12-month average $y_t^{\sim}$ to generate an estimate of the combined seasonal and irregular components $S \times I$:

$$\frac{L \times S \times C \times I}{L \times C} = S \times I = \frac{y_t}{y_t \sim} = z_t \tag{3}$$

The irregular component I is eliminated by computing the average values of $S \times I$ corresponding to the same month. Suppose that there are 48 months of traffic volume data. The average values of $S \times I$ for the same month are computed as follows:

$$average\ value\ z_1^{\sim} = \frac{1}{4}(z_1 + z_{13} + z_{25} + z_{37}) \tag{4}$$

$$average\ value\ z_2^{\sim} = \frac{1}{4}(z_2 + z_{14} + z_{26} + z_{38}) \tag{5}$$

. . . .

$$average\ value\ z_{12}^{\sim} = \frac{1}{4}(z_{12} + z_{24} + z_{36} + z_{48}) \tag{6}$$

The irregular fluctuations are smoothed out by averaging the seasonal-irregular percentages z_t for each month.

The twelve average values $z_1^{\sim}, \ldots, z_{12}^{\sim}$ are the estimates of the seasonal indices. The sum (T) of the twelve average values $z_1^{\sim}, \ldots, z_{12}^{\sim}$ is usually close to 12. If the sum of the twelve averages is not close to 12, the average values should be adjusted as follows:

$$adjusted\ average\ z_1^{\wedge} = \frac{z_1^{\sim} \times 12}{T} \tag{7}$$

$$adjusted\ average\ z_2^{\wedge} = \frac{z_2^{\sim} \times 12}{T} \tag{8}$$

. . . .

$$adjusted\ average\ z_{12}^{\wedge} = \frac{z_{12}^{\sim} \times 12}{T} \tag{9}$$

These twelve adjusted average values $z_1^{\wedge} \ldots z_{12}^{\wedge}$ are the seasonal indices. The original series y_t can be deseasonalized by dividing each value in the series by its corresponding seasonal index.

The link volume trend is investigated after the observed link volumes are deseasonalized using the *ad hoc* smoothing model. The time series deseasonalized link volumes are assumed to have a linear form of trend, growing by a constant absolute amount over time. A simple linear regression model is applied to predict the long-term growth pattern of the deseasonalized link volumes in each link. The linear regression model is formulated into the following form:

$$DSVOL = \alpha \bullet MONTH + \beta \tag{10}$$

where

$DSVOL$ = *deseasonalized link volumes in each link, and*
$MONTH$ = *the number of months associated with link volumes.*

The first month in the time series is assigned to value 1. The value is incremented by 1 for each month. This time variable is used as an explanatory variable in the simple regression model for each link. Regression coefficients are interpreted as the trends of the deseasonalized link volumes.

Any statistical analysis software can be used to codify the decomposition method. This research uses the UNIX version of the Statistical Analysis System (SAS) software to codify the *ad hoc* smoothing model and the linear regression model. The two models are structured as two sequentially connected SAS codes: the seasonal index code and the trend index code.

5. ANALYSIS AND RESULTS

5.1 Traffic Count Data

Traffic volumes contain trend, seasonal variation, monthly variation, daily variation, hourly variation, and sub-hourly variation. Traffic counts are a major source for traffic volume data. Caltrans continuously collects traffic counts at designated traffic count stations installed on freeways and state highways. Caltrans' STATEWIDE traffic count program provides two types of traffic volumes computed from traffic count data: hourly-based traffic volumes and monthly average daily traffic volumes. Our study is based on the monthly average daily traffic volumes to exclude sub-hourly, hourly, daily, and monthly variations from traffic volumes.

Monthly average daily traffic volumes from October 1986 to December 1994 were obtained from 138 traffic recorder stations of Caltrans District 7. Figure 1 shows traffic recorder stations in the Los Angeles highway network. Variational features of time series traffic volumes such as trend or seasonality may be identified after plotting the traffic volumes against time. Thus, monthly average daily traffic volumes from October 1986 to June 1993 are standardized by setting the column of September 1992 to 100, and then by converting other months' traffic volumes relative to the September 1992's column.[2]

[2] The standardized values are good indicators in presenting seasonal and trend variations of traffic volumes collected from different locations. We may use the total number of traffic volumes instead of the standardized values. Suppose that traffic volumes collected from a few links dominate the total number of traffic volumes of all links. Variations of the traffic volumes from the small number of major links will dominate the variations of the total traffic volumes. The use of standardized values prevents this problem. All links equally influence seasonal and trend variations of the mean standardized value. This approach is applicable, even though the number of observations (traffic volumes) varies month by month.

The number of observations varied throughout the study months from October 1986 to June 1993. The month of September 1992 had the highest number of observations. Thus, the month of September 1992 is selected as the standard month.

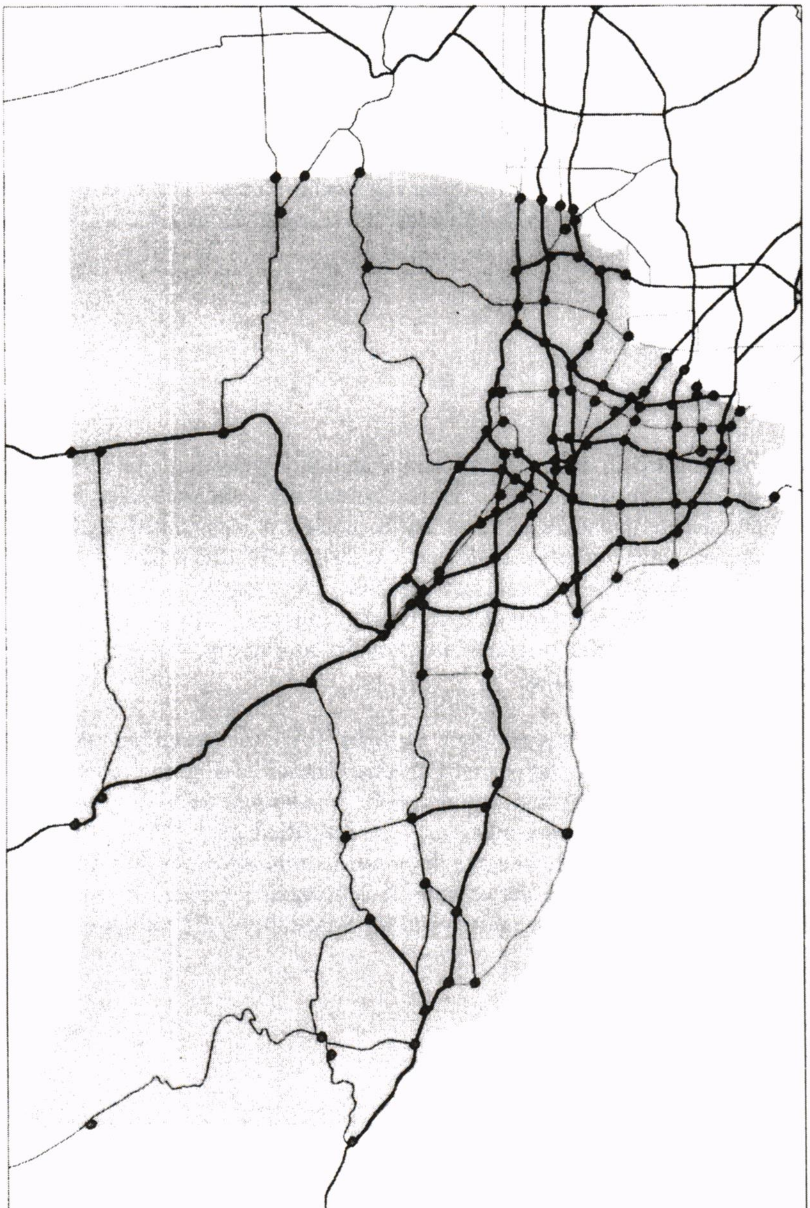

Figure 1: Los Angeles Highway Network and Traffic Count Stations

Figure 2 summarizes the mean, standard deviation, minimum value, and maximum value of the standardized values derived from the monthly average daily traffic volumes between October 1986 and June 1993. "AVE" stands for the mean value. "USTD" and "LSTD" stand for the upper and lower values of one standard deviation, respectively. "MIN" and "MAX" stand for the minimum and maximum values of the standardized values, respectively. The figure shows a clear feature of seasonality and trend embedded in the traffic volumes from October 1986 to June 1993.

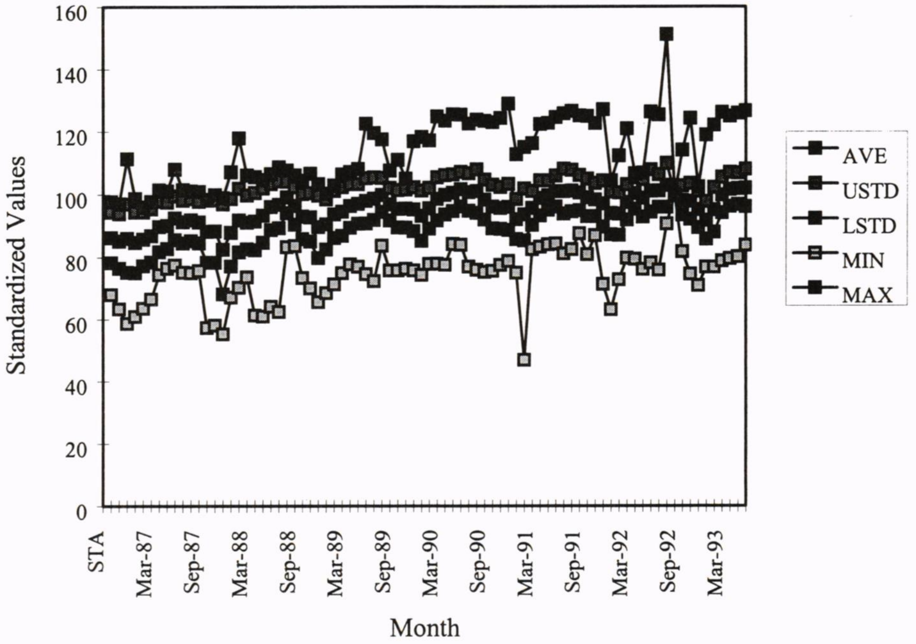

Figure 2. Average, Upper-Limit, Lower-Limit, Maximum, and Minimum Values of Standardized (100) Monthly Average Daily Traffic Volume Data from October 1986 to June 1993

5.2 Seasonal Indices

The decomposition method introduced in Section 4 is applied to compute seasonal and trend indices from traffic volumes of 276 directed links. The *ad hoc* smoothing model is employed to compute the seasonal indices from monthly average daily traffic volumes between October 1986 and June 1993. Table 1 shows part of seasonal parameter estimates, representing the seasonal indices of 276 directed links. Table 2 presents means, maximum values, minimum values, and standard deviations of seasonal indices of 276 directed links. The mean value of seasonal indices in each month is drawn in Figure 3. The figure demonstrates the seasonal pattern of Los Angeles highway traffic volumes.

Table 1. Seasonal Parameter Estimates of 276 Directed Links

OBS	ROAD	STATION	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
35	5	52N	0.952	0.923	0.977	1.016	1.027	1.035	1.039	1.061	1.017	0.996	0.972	0.958
36	5	52S	0.967	0.936	0.973	1.011	1.003	1.033	1.018	1.052	1.015	0.994	0.977	0.965
37	5	722N	0.959	0.977	0.997	1.012	1.014	1.039	1.044	1.045	1.001	0.978	0.978	0.980
38	5	722S	0.973	0.980	0.996	1.012	1.011	1.020	1.029	1.026	1.000	0.991	0.985	0.980
|	|	|	|	|	|	|	|	|	|	|	|	|	|	|
|	|	|	|	|	|	|	|	|	|	|	|	|	|	|
273	71	105N	0.956	0.987	0.997	1.028	1.017	1.024	0.998	1.004	1.004	1.001	0.976	1.020
274	71	105S	0.970	0.993	0.996	1.028	1.016	1.013	0.985	1.000	0.998	1.011	0.990	1.006
275	90	198E	.	0.986	.	.	0.997	.	.	1.012	.	.	0.996	0.935
276	90	198W	.	0.986	.	.	0.997	.	.	1.012	.	.	0.996	0.936

Table 2. Means, Maximums, Minimums, and Standard Deviations of Seasonal Indices

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
MEAN	0.958	0.967	0.990	1.016	1.018	1.028	1.018	1.026	1.005	0.989	0.986	0.980
MAX	1.051	1.105	1.134	1.299	1.380	1.173	1.244	1.211	1.089	1.112	1.180	1.169
MIN	0.822	0.806	0.840	0.901	0.925	0.846	0.715	0.759	0.766	0.767	0.847	0.757
STD	0.037	0.040	0.031	0.033	0.049	0.030	0.045	0.051	0.033	0.029	0.027	0.052

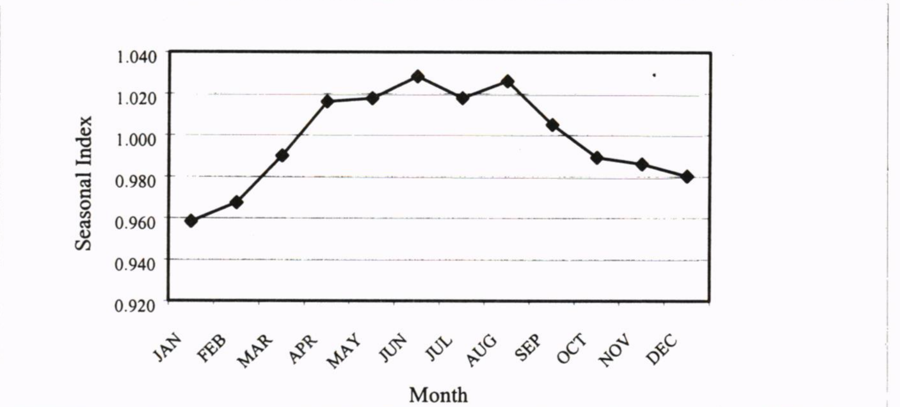

Figure 3. The Mean Values of Seasonal Indices

5.3 Trend Indices

The simple linear regression model is used to identify the long-run trends of deseasonalized traffic volumes. We assign value one to the month of October 1986, and increase this value by one for each month until the month of June 1993. We assume this index as a time variable. This time variable is used as an explanatory variable in the linear regression model.

The monthly average daily traffic volumes from October 1986 to June 1993 are adjusted by using the seasonal indices. The deseasonalized average daily traffic volumes are used as a predictor variable to execute the simple regression model. The slope of the simple regression model for each link is computed and regarded as the long-term trend for the link. Table 3 shows part of trend indices. Each row represents a link. There are 292 directed links in the transportation network. The first column, "OBS," stands for the identification number of observations. "Route" stands for the identification number of freeways and roadways. Route 101 represents Ventura Freeway. "Dir" stands for directions of routes. "S," "N," "E," and "W" stand for south, north, east, and west, respectively. "F_Z" and "T_Z" stand for "from zone" and "to zone," respectively. "Trend" stands for the slope that represents the long-term trend of deseasonalized average daily traffic volumes for the link. Trend indices represent the annually increasing or decreasing number of vehicle trips in links.

Out of 276 links, 155 links have positive values of trend indices, and 83 links have negative values. The remaining 38 links have insufficient data sets so that there are no values of trend indices. Figure 4 and 5 present the distribution of positive and negative values of trend indices, respectively.

Table 3. Trend Indices

OBS	Route	Station	Dir	F_Z	T_Z	Trend	OBS	Route	Station	Dir	F_Z	T_Z	Trend
1	101	758	S	1	4	-38.5067	41	118	422	E	27	28	107.8338
2	101	758	N	4	1	-16.7254	42	118	422	W	28	27	86.7827
3	33	433	S	2	3	-2.40551	43	118	755	E	28	29	129.5966
4	33	433	N	3	2	-3.67563	44	118	755	W	29	28	89.15135
5	33	753	S	3	4	6.226265	45	101	740	S	9	14	84.91133
|	|	|	|	|	|	|	|	|	|	|	|	|	|
|	|	|	|	|	|	|	|	|	|	|	|	|	|
289	1	6	S	102	104	0.111111	291	1	437	S	104	105	158.25
290	1	6	N	104	102	47.36667	292	1	437	N	105	104	143.225

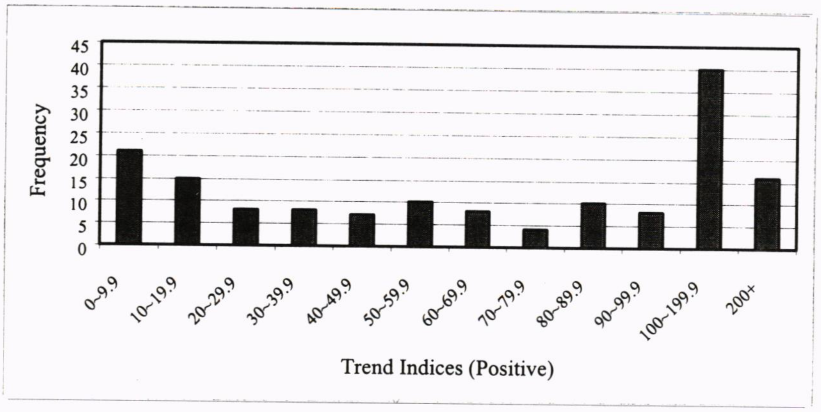

Figure 4. The Distribution of Positive Values of Trend Indices

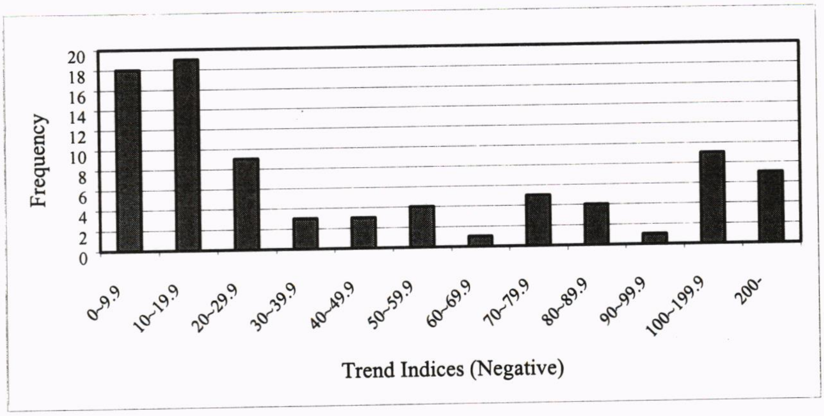

Figure 5. The Distribution of Negarive Values of Trend Indices

Figure 4 shows that trend indices of fifty-six directed links are more than 100. Traffic volumes of the links are rapidly increasing. The highest frequency of positive trend indices is shown in the range of 100 and 199.9. Figure 5 shows that many links have smaller values among negative trend indices. The highest frequency of negative trend indices is shown in the range of –10 and –19.9. The result shows there are more links whose traffic volumes are increasing than decreasing in the Los Angeles transportation network.

6. CONCLUSIONS

This research developed the decomposition method to identify seasonal and trend variations of Los Angeles highway traffic volumes collected by Caltrans District 7 during the period between October 1986 and June 1993. The ad hoc smoothing model is employed to compute seasonal indices from monthly average daily traffic volumes. The simple linear regression model is used to identify the long-run trends of deseasonalized traffic volumes.

The results demonstrate the applicability of the decomposition method in identifying seasonal and trend indices from time-series traffic volumes. The ad hoc smoothing successfully captures the seasonal variations of traffic volumes. The linear regression model provides positive or negative values of trend indices of deseasonalized traffic volumes. The seasonal and trend indices may be used as important information when traffic volumes before events are compared to those after events. The trend indices also provide some information regarding future highway bottlenecks and/or changes of land-use patterns.

REFERENCES

Ahmed, Mohamed S. and Cook, Allen R. (1979) Analysis of Freeway Traffic Time-Series Data By Using Box-Jenkins Techniques. **Transportation Research Record 722**, 1-9.

Benjamin, Julian. (1986) A Time-Series Forecast of Average Daily Traffic Volume. **Transportation Research**, Vol. 20A, No. 1, 51-60.

Faghri, Ardeshir and Chakroborty, Partha (1994) Development and Evaluation of a Statistically Reliable Traffic Counting Program. **Transportation Planning and Technology**, Vol. 18, No. 4, 223-237.

Granger, C. W. J. (1989) **Forecasting in Business and Economics**. Academic Press, Inc, Boston.

Hamed, Mohammad M., Al-Masaeid, Hashem R. and Bani Said, Zahi M. (1995) Short-Term Prediction of Traffic Volume in Urban Arterials. **Journal of Transportation Engineering**, Vol. 121, No. 3, 249-254.

Hartgen, David T. and Lemmerman, John H. (1983) Streamlining Collection and Processing of Traffic Count Statistics. **Transportation Research Record 928**, 11-18.

Johnson, Aaron C. Jr., Johnson, Marvin B. and Buse, Rueben C. (1987) **Econometrics: Basic and Applied.** MacMillan Publishing Company, New York.

Kennedy, Peter (1992) **A guide to Econometrics**. The MIT Press, Cambridge.

Lardaro, Leonard (1993) **Applied Econometrics**. Harper Collins College Publishers, New York.

Moorthy, C. K. and Ratcliffe, B. G. (1988) Short Term Traffic Forecasting Using Time Series Methods. **Transportation Planning and Technology**, Vol. 12, 45-56.

Newell, Gordon F. (1967) Stochastic Properties of Peak Short-Time Traffic Counts. **Transportation Science**, Vol. 1, No. 3, 167-183.

Nihan, Nancy L. and Holmesland, Kjell O. (1980) Use of the Box and Jenkins Time Series Technique in Traffic Forecasting. **Transportation**, Vol. 9, No. 2, 125-143.

Pindyck, Robert S. and Rubinfeld, Daniel L. (1991) **Econometric Models and Economic Forecasts**, McGraw-Hill, Inc, New York.

Ramanathan, Ramu. (1992) **Introductory Econometrics with Applications**. Harcourt Brace Jovanovich College Publishers, Fort Worth.

Ritchie, Stephen G. (1986) A Statistical Approach to Statewide Traffic Counting. **Transportation Research Record 1090**, 14-21.

Sharma, Satish C., Gulati, Brij M. and Rizak, Samantha N. (1996) Statewide Traffic Volume Studies and Precision of AADT Estimates. **Journal of Transportation Engineering**, Vol. 122, No. 6, 430-439.

Sharma, Satish C. and Oh, Jin Y. (1989) Prediction of Design Hourly Volume from Road Users' Perspective. **Journal of Transportation Engineering**, Vol. 115, No. 6, 646-660.

Southern California Association of Governments (SCAG). (1993) **1991 Southern California Origin-Destination Survey: Summary Findings**. Southern California Association of Governments, Los Angeles.

Sparks, Gordon A. (1976) The Unpublished Schedule of Urban Peak Period Traffic. **Transportation Science**, Vol. 10, No. 3, 300-315.

Transportation Research Board. (1985) **Highway Capacity Manual**. Transportation Research Board, Washington, D.C.

Vaughan, Rodney J. (1970) The Distribution of Traffic Volumes. **Transportation Science**, Vol. 4, No. 1, 97-110.

Vaziri, Manouchehr, Hutchinson, John and Kermanshah, Mohammad (1990) Short-Term Demand for Specialized Transportation: Time-Series Model. **Journal of Transportation Engineering**, Vol. 116, No. 1, 105-121.