Jordan Journal of Civil Engineering, Volume **8**, No. **3**, **2014**

Traffic Volume Forecasting for Rural Roads in Jordan

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ABSTRACT

The accuracy of traffic forecasting is a point of considerable importance to the effective allocation of limited resources. Thus, reasonable and accurate forecasting methods should be developed to help engineers and planners make rational decisions and reduce probable associated risks. This study investigated the performance of three forecasting methods: aggregate regression, disaggregate trend and empirical Bayesian analysis. To accomplish this objective, traffic volumes for major rural roads in 1996 through 2004 were obtained from the Ministry of Public Works and Housing of Jordan. For each city or zone, cross-sectional data on socio-economic and demographic variables were collected.

Multivariate regression analysis was carried out to develop mathematical relationships that could have practical applications. The results indicated that the products of populations-to-roadway length ratio, number of employees, fuel consumption, number of buildings and road type significantly influenced traffic interchange between cities or zones. For Jordan conditions, the linear model was recommended. Trend models, having exponential form, were also developed. Performance analysis indicated that aggregate regression and empirical Bayesian analysis provided comparable results. In contrast, the performance of trend method was considered to be poor. Finally, while these results are related to Jordan, they possibly apply elsewhere as well.

KEYWORDS: Traffic forecasting, Trend analysis, Regression, Bayesian method, Rural roads, Jordan.

INTRODUCTION

In traffic volume studies, there is a need to estimate the average annual daily traffic volume (AADT) at highway level. Forecasting traffic volume is needed for a variety of purposes; including planning, design, priority setting and improvement, as well as allocation of expenditures for maintenance. Also, the AADT is needed to predict some events related to traffic volume such as the number of accidents or other environmental issues. Today, the accuracy of traffic forecasting is a point of considerable importance to efficient and effective allocation of scarce funds. Thus, reasonable and accurate forecasting methods should be developed to help engineers and planners make sound decisions and reduce probable financial and economic risks.

For rural roads, both multivariate regression and trend projection analyses are normally used for estimating future traffic volumes. These methods have been developed and tested in many countries (Al-Masaeid, 1992; Saha and Fricker, 1988; Mohamad et al., 1988; Michael, 2004; Armstrong, 1984). In practice, different regression models have been developed and tested; including aggregate and disaggregate statistical models developed to forecast traffic volumes on rural locations in Indiana's state

Accepted for Publication on 19/3/2014.

highway network (Saha and Fricker, 1988; Mohamad et al., 1988), elasticity based regression models developed to forecast traffic volumes on the rural highways in New York State (Neveu, 1982) and cluster regression analysis developed to estimate traffic volume on rural local roads in Georgia (William, 2000). Both demographic and economic predictor variables were used in the model development. In the selection of a specific model, several criteria should be observed, such as simplicity and reliability of the model and availability of data.

In trend analysis, analysts can modify the extrapolation based on the experience and knowledge of the route, state or region. Trend analysis assumes that past trend will continue into the future. With this assumption, the past data can be used to forecast AADT volume to a specific year in future. In reality, extrapolation methods rely solely on historical data. Some studies indicated that sophisticated extrapolation techniques have had negligible pay-off for accuracy in forecasting (Armstrong, 1984). However, more sophisticated methods may be expected to produce more accurate forecast and provide better assessment of uncertainty if properly used by experts. In trend analysis, it is important to examine the trends in past data to ensure that the future trend has consistent results. Failing to do so could produce large errors in the volume estimates. The accuracy of the projections is influenced by several factors; including the time period of the forecast and the amount of economic activities in the region (Mommott, 1983; Gerard et al., 2007; Parthasarathi and Levinson, 2010). Furthermore, trend analysis can not anticipate unpredictable or random events that could substantially affect traffic volume estimates.

In fact, both regression and trend analyses are considered as deterministic methods. Accordingly, some researchers suggested the use of probabilistic approaches to account for uncertainty associated with estimation of traffic volumes. The reason for adapting probabilistic approach is that the estimation of the traffic volume from historical data is restricted by the dynamic change in population, employment, energy problems, economic activity and demographic changes among other factors. For example, empirical Bayesian approach was utilized in some studies to predict traffic crashes (Al-Masaeid et al., 1993), traffic volume on a highway section level (Al-Masaeid, 1992; Zhing et al., 2006) or in modeling trip generation rate for USA (Dey and Fricker, 1994).

The main objective of this study was to develop and investigate the performance of traffic prediction models; multivariate regression, trend projection, and empirical Bayesian analysis. To accomplish this task, data on average daily traffic volumes (ADT) for major rural roads in Jordan for nine years, 1996 through 2004, were obtained from the Ministry of Public Works and Housing of Jordan. Other related data, such as demographic and socioeconomic variables, were collected from related sources. Investigation of performance of the developed models was carried out to identify and recommend such models that could have practical applications for estimating future traffic volumes on rural roads.

BACKGROUND

Jordan is located in the heart of the Middle East and is considered as a transport hub for the surrounding countries (see Figure 1). The country consists of twelve governorates. In each governorate, there is a major city. Major rural roads connect these cities with each other. In addition, international rural roads straddle the country and connect it with surrounding countries. The Ministry of Public Works and Housing is responsible for planning, design and construction of these roads. The ministry usually conducts traffic volume studies to determine traffic volume on each road. These volumes are based on the standard 48-hour traffic counts in each year. Volume counts are usually conducted during May-June at the end of spring season and in September-October months. Literature (Garber and Hoel, 1988) indicated that during these months the average daily traffic volume (ADT) is approximately equal to the average annual daily traffic volume (AADT).

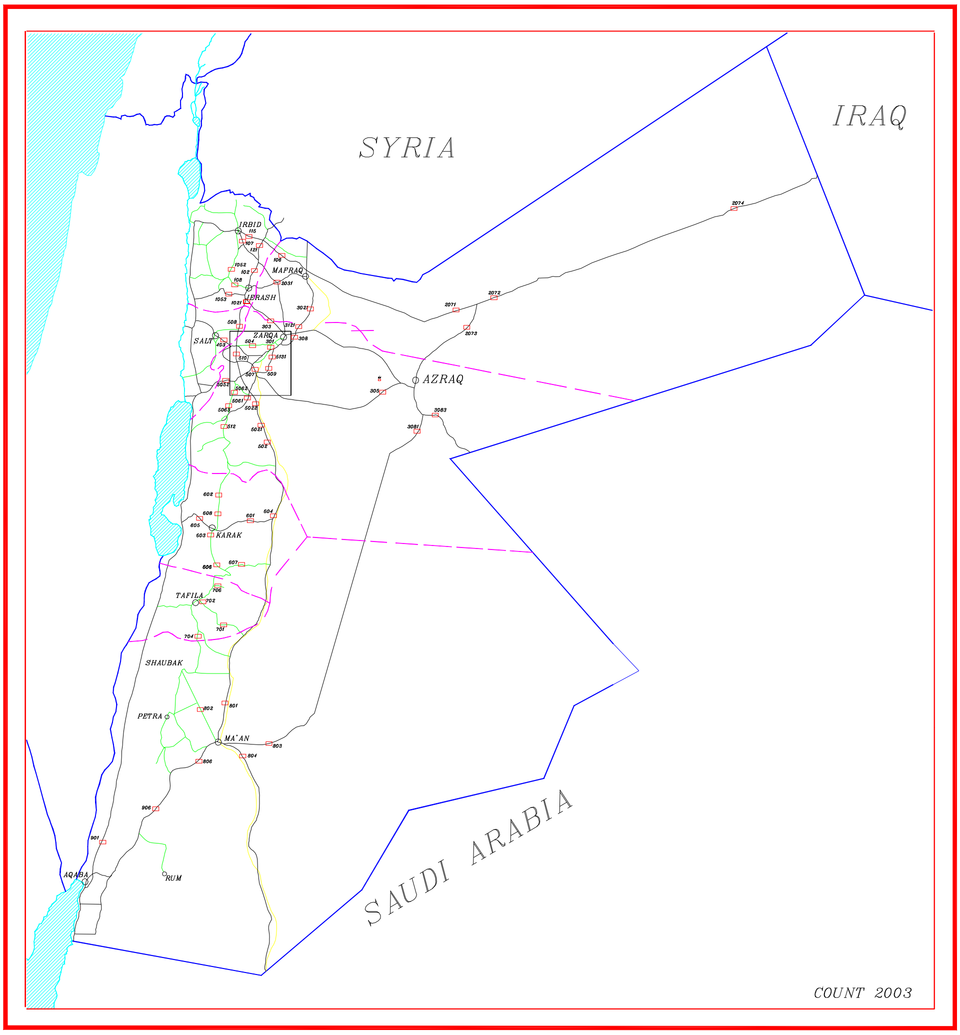

Figure (1): Jordan's rural road network and locations of counting stations

In Jordan, all traffic counts are considered as coverage counts. Therefore, these counts do not account for seasonal variations; consequently the obtained volumes represent ADT rather than AADT. In estimating future traffic volume for planning or maintenance priority setting purposes, traffic engineers determine traffic volume based on projection approach, assuming a growth rate of 3 to 5 per cent. However, these estimates sometimes provide unreliable results. Furthermore, it was observed that some traffic volumes on rural roads undergo dramatic changes especially on the international highways due to the political situations in the whole area.

METHODOLOGY

As mentioned before, the performance of three forecasting methods will be investigated in this study. In the first method, multivariate aggregate regression analysis was carried out to develop forecasting models for estimating traffic volume as a function of socioeconomic and demographic variables. In the analysis, a correlation matrix was established to identify variables that had an effect on traffic volume and to check possible multicollinearity between pairs of independent variables. Data for 1996 through 2001 were used in model development, while data for years 2002, 2003 and 2004 were used to test the model performance.

In the second method, disaggregate trend analysis was performed to estimate traffic volume based on historical data. Researchers indicated that traffic increases exponentially (Sharaf, 1984). Similar to multivariate analysis, traffic data for 1996 through 2001 were used in model development at roadway level.

In the third method, empirical Bayesian analysis was adopted to estimate traffic growth rate. The reason for adapting this method is that the estimation of the mean growth rate (m) from historical data is restricted by the dynamic change in population, employment, energy problems, vehicle registration and demographic changes among other factors. Therefore, the estimation of the mean growth rate (m) at any highway section is uncertain. For this reason, the mean growth rate is considered as a random variable.

The Bayesian approach has the capability to augment the prior knowledge with the most recent limited information (sample likelihood function) to form a refined distribution called posterior distribution. The posterior distribution is the basis for predicting the mean growth rate at highway section level.

Based on the previous study (Al-Masaeid, 1992), the traffic growth rate (g) is normally distributed over all similar road sections with unknown mean (m) and standard deviation (σ). If f'(m,σ) is the prior joint probability density function of m and σ, and L(m,σ,g1,g2,…,gn) is the likelihood function of normal process, then the posterior joint density function of m and σ is (Benjamin and Cornell, 1970):

$$f''(m, \sigma) = N * f'(m,\sigma) * L(m,\sigma,g1,g2,\ldots,gn) \qquad (1)$$

where:

N = normalizing factor.

σ = standard deviation of the growth rate.

n = size of the likelihood sample.

The marginal distribution of the posterior mean m has a t- distribution with n"– 1 degrees of freedom and parameters n'', $\bar{g}''$ and s'', as follows:

$$f''(m,\sigma) = (1\sqrt{\pi}) \times (1/s'')\sqrt{(n''/(n''-1))} \times (\Gamma(n''/2)/\Gamma((n''-1/2) \times \left[1 + n''/(n''-1)(m-\bar{g}''/s'')^2\right]^{-n''/2} \qquad (2)$$

Posterior distributed parameters are estimated from the parameters of the prior distribution (n', $\bar{g}$, and s'^2) and sample likelihood function (n, $\bar{g}$, s^2) as follows:

$$n'' = n + n' \qquad (3)$$

$$\bar{g}'' = (n\bar{g} + n'\bar{g}')/n'' \qquad (4)$$

$$S''^2 = \left\{\left[(n-1)s^2 + n\bar{g}^2\right] + \left[(n'-1)s'^2 + n'\bar{g}'^2\right] - n''\bar{g}'' \right\}/(n''-1) \qquad (5)$$

where:

n'' = posterior sample size.

$\bar{g}''$ = posterior mean.

S''^2 = posterior variance.

n' = sample size of prior information.

$\bar{g}'$ = mean of prior information.

s'^2 = variance of prior information.

n = sample size of the most recent information (likelihood sample).

$\bar{g}$ = sample mean (likelihood sample).

s^2 = sample variance (likelihood sample).

The posterior mean and variance of m are:

$$E(m) = \bar{g}'' \qquad (6)$$

$$Var(m) = s''^2 \left[n''-1/n''(n''-2) \right] \quad (7)$$

Despite the fact that prior knowledge or distribution provides useful information, the effect of prior information diminishes as it is updated with more observed data to form the posterior distribution (Al-Masaeid, 1997). Obviously, prior parameters are estimated from population of rural major roads. In this sense, it is advisable to classify major roads into: international and intercity roads. This classification is necessary to have mean growth rate with low variability (Al-Masaeid et al., 1993). In the next step, prior parameters are augmented with a given road data; i.e., sample likelihood, to form posterior distribution for the road under consideration.

In this method, traffic volume at a given road section is estimated in two steps. In the first step, the Bayesian approach can be applied to estimate posterior mean of the growth rate E(m) and its variance VAR (m). In the second step, the posterior mean and the present or base-year ADT are substituted into the following equation to obtain an estimate of future volume in the coming year (Najah, 2006):

$$ADT_f = ADT_p * e^{mt} \quad (8)$$

where:

ADT_f and ADT_p = annual average daily traffic volumes in future and base-year, respectively.

e = the base of the natural logarithm.

t = the time period in years between future and base-year.

DATA COLLECTION

Two sets of data were collected in this study. The first data set included average daily traffic volumes for rural roads. These volumes were obtained from yearly book reports (MPWH, 1996-2004) of the Ministry of Public Works and Housing (MPWH) of Jordan. Traffic volumes for years 1996 through 2004 were used in the study. As mentioned earlier, these volumes represented the average daily traffic volumes obtained from standard 48-hour traffic counts. For economic purposes, volume counts are not conducted on a yearly basis for some stations. In this study, count stations with incomplete data were not considered in the analysis.

Table 1. Descriptive statistics of included variables

Variable	Unit	symbol	Mean	Maximum	Minimum
Traffic volume	veh./day	ADT	7497.55	36160	570
Population	persons	P	387137.6	2085140	67,500
Employees	persons	E	56232.69	810043	3030
Fuel consumption	million liters	F	186335.2	1401940	10780
Establishments	number	Es	103.14	902	11
Buildings	number	Bl	862.43	4866	54
Residentials	number	Res	1435.30	12267	47
Vehicle Registration	number	Vr	32495.43	419235	900
Length of Road Network	km	L	610.2813	1409	32

The second data set consisted of socio-economic and demographic information. These data were obtained from the Jordan Department of Statistics. The socio-economic characteristics included information on the number of employees, the number of commercial and service establishments, the number of registered vehicles and fuel consumption in each governorate. The collected demographic data consisted of population of each city connected by major road and the number of residential and non-residential buildings in each governorate. Other data such as length of road network in each governorate, type and length of major road between cities, were also collected. Table 1 presents the statistical characteristics of the data collected.

ANALYSIS AND MODELING RESULTS

Correlation Analysis

Previous studies have indicated that traffic interchange between two zones depends on measures of intensities of activities in these zones. For example, aggregate demand model (Jonson, 1982; Papacostas and Prevedouros, 1993) used the product of populations in both zones for estimating traffic interchange between the two zones. In this study, the same results were obtained (Najah, 2006); that is, traffic volume between two cities or zones is correlated to the product of their populations. However, for roads connecting more than two cities, different options were investigated. In Figure 2, station # 102 counted traffic volumes between Irbid and Jerash and between Irbid and Amman. Thus, three forms of intensities for each variable were tested in this study. These include:

$$SPP = (PI*PJ) + (PI*PA) \quad (9)$$

$$PSP = (PI+PJ) * (PI+PA) \quad (10)$$

$$PPP = (PI*PJ) * (PI*PA) \quad (11)$$

where:

PI, PJ and *PA* = population of Irbid, Jerash and Amman, respectively.

SPP = sum of products of populations.

PSP = product of the sums of populations.

PPP = product of the population products.

The correlation analysis indicated that traffic volume on a given road section is strongly correlated with the sum of products of populations (see Table 2). The same results were obtained for other intensities such as employees, fuel consumption, number of buildings or vehicle registration.

Table 2. Correlation matrix for population intensities

Variable	ADT	SPP	PSP	PPP
ADT	1.000			
SPP	.790	1.000		
PSP	-.071	-.008	1.000	
PPP	-.050	-.005	.984	1.000

The correlation analysis also revealed that traffic volumes are strongly and positively correlated with the product of populations (POP), product of employees (PE) and product of populations-to-roadway length ratio (POP/D), (see Table 3). These results are logical, since large cities with high employment demand tend to be more attractive for trips. On the other hand, long distance between a pair of cities would cause impedance effect. Further investigation of Table 3 indicates that the products of vehicle registration (PVr), fuel consumption (PF), number of buildings (PBl) and number of establishments (PEs) have positive correlation with traffic volume. Nevertheless, the use of these variables in model development should be avoided whenever possible because of multicollinearity (Neter et al., 1985).

Table 3. Correlation matrix of the included variables

Variable	ADT	POP	PE	PF	PRes	PVr	L	POP/D
ADT	1.00							
POP	0.79	1.00						
PE	0.73	0.74	1.00					
PF	0.57	0.64	0.69	1.00				
PEs	0.56	0.71	0.79	0.91				
PBl	0.45	0.67	0.25	0.25				
PRes	0.47	0.67	0.28	0.25	1.00			
PVr	0.67	0.79	0.73	0.70	0.63	1.00		
L	0.41	0.51	0.34	0.65	0.44	0.51	1.00	
POP/D	0.83	0.86	0.59	0.38	0.55	0.602	0.28	1.00

Traffic Volume Regression Models

Regression analysis was carried out to develop models that are capable of predicting traffic volumes on rural major roads. Based on the analysis, the following models were obtained:

$$ADT=2080.75+0.44\ (POP/D)+0.17\ (PE)+2853\ (Type) \quad (12)$$

$$ADT=0.034\ (POP)^{0.83}(PE)^{0.24}(PF)^{-.51}(PBl)^{-.22}*10^{0.21Type} \quad (13)$$

where:

ADT = Average Daily Traffic, (vpd).

POP/D = product of populations-to-roadway length ratio.

D = length of road between a pair of cities, (km).

PE = employee product.

POP = population product.

PF = fuel consumption product.

PBl = buildings product.

Type = type of major road (1 for international roads and 0 otherwise).

The linear model in Equation 12 and all parameters were found to be significant at 95% confidence level (N=82, R^2=0.805, F =107.45, p=0.0001). The model indicated that traffic volume on a road between two cities is proportional to the product of their populations and inversely to the length of roadway between them. However, the product of populations-to- roadway length ratio should be substituted by the sum of products of populations-to-road length ratio in the case of more than two cities. Also, traffic volume is proportional to the product of employees in both cities.

Model in Equation 13 and its parameters were found to be significant at 95% confidence level (N=82, R^2=0.82, F=66.86, p=0.0001). Despite of the fact that this multiplicative model explained about 82 percent of traffic volume variations; however, this model contains exponent coefficients with algebraic signs that are the opposite of those expected from theoretical considerations. For example, the increase in fuel consumption and number of buildings in each city would most likely increase the traffic on the road connecting them. Obviously, serious multicollinearity (see Table 3) among the independent variables may be the essential reason for this unrealistic interpretation. In general, the presence of multicollinearity among independent variables does not inhibit our ability to obtain a good fit nor does it tend to affect predictions, provided these predictions are made within the region of observations (Neter et al., 1985).

Although each of the linear and multiplicative models explained more than 80 per cent of traffic volume variations, the analysis in this study recommended the use of the linear model to predict traffic volumes on rural roads in Jordan. In fact, the developed linear model is simple in form, logical in coefficient signs, realistic in interpretation and requires less detailed data. For a given road, the type and distance between cities are normally known constants; thus the planner needs to know population and employee products to estimate future traffic volume. Furthermore, the linear model and its independent variables are consistent with previous models developed for rural roads (Al-Masaeid et al., 1998; Saha and Ficker, 1988).

Trend Analysis

This method is suitable for road sites without accurate city attributes such as international roads that connect Jordan with adjacent countries. Disaggregate regression analysis was performed to develop trend models using traffic data of 1996 through 2001. Based on the analysis, an exponential model was the best to fit the data for each road segment. This result is compatible with previous findings in trend analysis (Sharaf, 1984; Mommott, 1983). Table 4 presents some of the developed models for international roads in Jordan. Clearly, the coefficient of determination (R^2) varies from 48 to 96 per cent. However, when the developed models in Table 4 were applied to predict traffic volumes for years 2002, 2003 and 2004, the resulting absolute errors ranged from 12 to 46 per cent. Thus, the performance of trend method in predicting future traffic on international roads is questionable, since it could result in considerable errors.

Table 4. Disaggregate models for selected roads

Road name	Model	R^2
Amman/Zarqa	$ADT_f = 0.75*ADTp*e^{0.114t}$	0.86
Azraq/Alumary	$ADT_f = 0.42*ADTp*e^{0.248t}$	0.89
Rumtha/Just University	$ADT_f = 0.78*ADTp*e^{0.07114t}$	0.77
Aqaba/Al Darreh	$ADT_f = 0.83*ADTp*e^{0.0180t}$	0.81
Amman/Airport	$ADT_f = 0.73*ADTp*e^{0.0.125t}$	0.58
Karak/Amman	$ADT_f = 0.62*ADTp*e^{0.122}$	0.96
Amman/Aqaba	$ADT_f = 2.94*ADTp*e^{0.212t}$	0.53
Amman/Ma'an	$ADT_f = 0.70*ADTp*e^{0.134t}$	0.48

Bayesian Analysis

As stated earlier, both posterior mean and present average daily traffic volume could be substituted in Equation 8 to estimate future traffic volume. In the analysis, roads were divided into two types; intercity roads and international ones. For each type of road, traffic data of 1996 and 1997 were used to compute prior parameters. For example, traffic volumes in years 1996 and 1997 for 29 sites were used to estimate prior parameters for intercity roads (see Table 5), and the results were: $n' = 29$ and $\bar{g}' = 0.127$. To estimate traffic volume in 2001 for station #108 in Table 5, a sample likelihood was drawn using traffic volumes and consequently growth rates for four years (1997-2000); $n=4$ and $\bar{g}' = 0.21$. Prior and sample likelihood parameters were augmented to compute posterior parameters, and the results were: $n=33$ and $\bar{g}'' = 0.14$. Both of the mean growth rate ($\bar{g}''$) and traffic volume in year 2000 were substituted into Equation 8 to predict traffic volume of 2001 for station #108.

Finally, Table 5 illustrates the predicted and actual traffic volumes for different stations during the period 2001 through 2003. Comparison of predicted and actual volumes revealed that the maximum error in prediction was 17.5% for station #903 in 2001, while the average absolute error for all stations during the period 2001 through 2003 was only about 7.5%. Therefore, the performance of the Bayesian method in predicting future traffic volumes is quite good.

Table 5. Bayesian results for selected road stations

Year	Variable Parameters	Station Number of Intercity Highways in Rural Areas					
		108	**601**	**603**	**902**	**302**	**903**
2001	Prior Parameters	$n'= 29$		$\bar{g}' = 0.127$	$s'^2=0.33$		
	Sample likelihood mean, $\bar{g}$	0.21	0.12	0.25	0.41	0.11	0.20
	Posterior mean, $\bar{g}''$	0.14	0.13	0.14	0.15	0.12	0.13
	Predicted ADT	4091	3066	6231	10026	7738	4553
	Actual ADT	4479	3285	5882	10061	8749	5520
	Error (%)	8.64	6.66	-5.95	0.34	11.55	17.50
		Station Number of Intercity Highways in Rural Areas					
		108	**312**	**601**	**704**	**3081**	**304**
2002	Prior Parameters	$n'= 29$	$\bar{g}' = 0.127$		$s'^2=0.33$		
	Sample likelihood mean, $\bar{g}$	0.21	0.29	0.14	0.02	0.26	0.16
	Posterior mean, $\bar{g}''$	0.13	0.15	0.13	0.12	0.14	0.13
	Predicted ADT	5113	9908	3737	1134	851	35897
	Actual ADT	5667	9881	4035	1221	892	35291
	Error (%)	9.76	-0.28	7.37	7.08	4.58	-1.7
		Station Number of Intercity Highways in Rural Areas					
		802	**501**	**305**	**507**	**606**	**1052**
2003	Prior Parameters	$n'= 29$	$\bar{g}' = 0.127$		$s'^2=0.33$		
	Sample likelihood mean, $\bar{g}$	0.38	0.08	0.37	0.06	-0.21	0.31
	Posterior mean, $\bar{g}''$	0.13	0.12	0.16	0.12	0.08	0.15
	Predicted ADT	1187	44799	7643	33048	579	13483
	Actual ADT	1361	39717	7000	31058	630	13031
	Error (%)	12.75	-12.79	-9.19	-6.41	8.07	-3.47

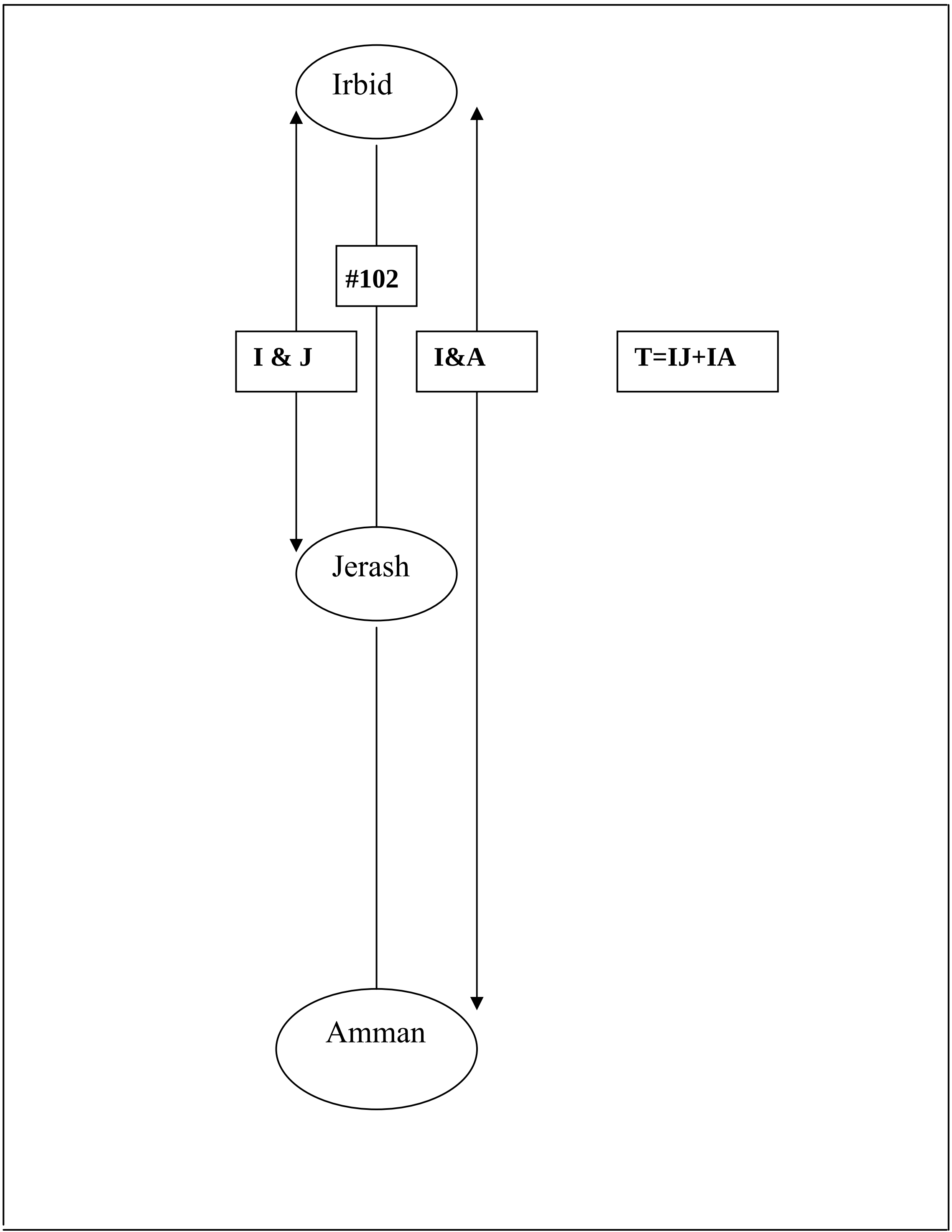

Figure (2): Traffic volume on Amman-Jerash-Irbid rural major road at station #102

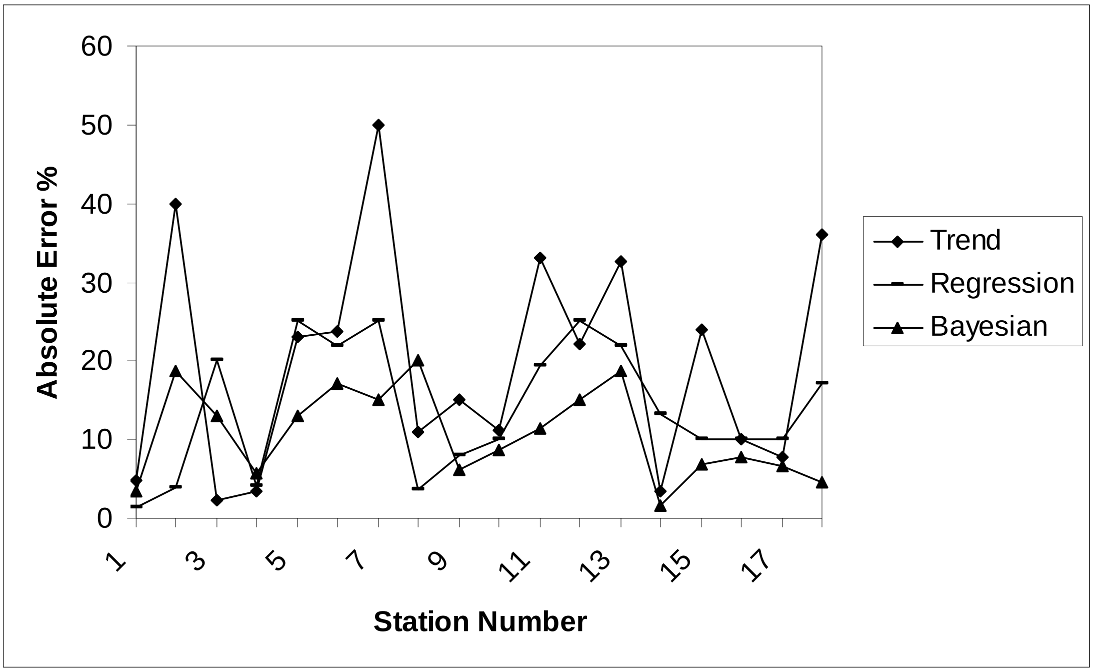

Figure (3): Performance of regression, trend and Bayesian methods

Performance of Forecasting Methods

The objective of performance analysis was to judge how each of the developed methods would perform under Jordan conditions. For this purpose, eighteen traffic stations on rural roads were selected based on the availability of socio-economic and traffic data. The predicted volumes for the year 2004 were computed and compared with the actual observed volumes for the same year. The results of forecasting, using the developed methods, are shown in Figure 3. The average absolute errors for trend, regression and Bayesian methods were 20, 14 and 11 per cent, respectively. Thus, analysis made in this study suggests the use of the Bayesian method to estimate future traffic volumes, especially for Jordan conditions, but possibly elsewhere as well. Furthermore, the outcomes of Bayesian and regression methods are comparable. Conversely, the trend method provided incorrect results with large margin of errors. Consequently, it is not recommended to use this method for forecasting volumes on rural roads in Jordan.

Finally, the developed models in this study could be used to predict volumes for short and medium planning purposes. For long term planning, population and employment level can be predicted and then used in the developed linear model. However, in the Bayesian approach, further studies are required to develop a procedure to determine suitable sample likelihood statistics.

CONCLUSIONS

Based on the results of this study, the following points were concluded:

1. Traffic volume between a pair of cities or zones is directly proportional to the product of their populations-to-roadway length ratio and to the product of their employees. Other variables, such as fuel consumption, vehicle registration and type of road have considerable influence on traffic interchange level between cities.
2. Forecasting linear and multiplicative aggregate regression models successfully explained the variations in traffic volume. For practical purposes,

the linear model is recommended for use under Jordan conditions.

3. All trend disaggregate models have an exponential form. They explain a large portion of variability in traffic volumes on rural roads. Nevertheless, their performances in predicting future traffic are poor.
4. Bayesian methodology developed in this study has provided reasonable and accurate traffic prediction results.
5. Although both Bayesian and regression methods have provided comparable results, more accurate results would be anticipated using the Bayesian method. In contrast, the use of trend method could result in large marginal errors, especially under Jordan conditions.

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