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Original scientific paper

A Stochastic Simulation Based Approach for Transportation Demand Forecast and Safety

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Abstract: Reliable traffic forecasts are critical for successful planning and financing of transportation projects. However, the accuracy evaluation results of the predicted traffic volumes often indicate significant discrepancies between the actual and predicted traffic volumes. These discrepancies are mainly due to both limitations and uncertainties in traffic demand forecasting models; therefore, researchers are continuously attempting to estimate the error and bias in traffic forecasts. To enhance these endeavors, a Monte Carlo simulation (MCS)- based approach is proposed in this paper as an alternative to the stochastic traffic demand forecast. This approach uses a sequential process to capture the effects of model inputs and variables on the error and bias in traffic demand forecasting. The approach proposed in this study was developed in three steps. First, the key factors causing errors and biases in traffic demand forecasts were identified based on a comprehensive review of traffic forecasting practices. Second, the effects of each variable on traffic volumes were quantified using MCS. Lastly, the statistical approach was constructed to provide an interval estimation of traffic volumes based on the findings of MCS. Through these steps, the inherent uncertainties in socioeconomic variables and heterogeneities in passenger behaviors with regard to traffic demand modeling were considered. Then, simulation experiments were conducted to investigate the applicability of the proposed approach to a real-world network. This approach is expected to reasonably capture the stochastic nature of future traffic volumes and quantify the risks associated with the error and bias in traffic demand forecasting. The findings of this study indicate that traffic forecasting practitioners can use the proposed approach with ease. The analysis results showed that the proposed approach clearly captured the changes in link traffic volumes owing to the statistical changes in the value of time (VOT). The experiments indicated that the uncertainties in VOT perceived by road users can be used to estimate the risks of toll road financing. The elasticity of traffic volume to VOT for each link, which can be used as a key input to the road project feasibility study, can be derived from the MCS-based analysis implemented in this study.

Keywords: demand forecast; Monte Carlo simulation; origin-destination (O-D); stochastic model; transportation; value of time

1 INTRODUCTION

Traffic volume forecasts largely depend on the accuracy of future development plans and input data as these factors directly affect every aspect of trip generation and traffic network (Chung and Chang, 2007; Flyvbjerg et al., 2005; Flyvbjerg et al., 2006). The magnitude of the error and bias in traffic forecasts cannot be exactly measured owing to the complex nature of traffic networks and traveler behaviors. Reliable traffic forecasts are required for the approval of transportation-infrastructure investment projects. Thus, efforts have continuously been made to estimate the error and bias in traffic forecasts in the past. Also, credibility can be quantified by measuring the error and bias associated with traffic forecasts. Currently, point estimation methods such as average annual daily traffic (AADT) are used to project future traffic volumes in South Korea. The point estimation methods converge traffic demand distributed in a zone of a certain area to a single point called a centroid. The calculation of the centroid may be erroneous owing to the discrepancies depending on the location of the centroid in the zone. Interval estimation methods can be a better alternative than the point estimation methods to estimate future traffic demand, considering the inherent error and bias in traffic demand forecasts. In the literature, two approaches of using interval estimation methods are proposed: i) the computer-intensive statistical method (Hugosson, 2005) and ii) the sensitivity-based method (Rodier, 2002). Notably, both approaches focus only on the inaccuracies of input data and do not examine the methodological aspects of the traffic demand forecasting process. In this paper, a Monte Carlo simulation (MCS)-based approach is proposed to estimate the risk in traffic demand forecasting considering the stochastic nature of traffic demand modeling.

Table 1 Ratio of actual predicted forecast traffic volumes

Classification	2003 update	2002 study
Minimum	0,15	0,31
Maximum	1,51	1,19
Mean	0,74	0,73
Number of case studies	68	32

Credibility in traffic forecasts has emerged as a considerable concern regarding the financing of road projects. As listed in Tab. 1, Standard & Poor's Rating Services (2003) suggests that traffic demand forecasts for toll road projects tend to show optimistic biases. This results into overestimation of traffic volumes by 20-30%. Flyvbjerg (2004) showed that the actual traffic volumes observed in the first year of operation differed from the predicted traffic volumes by 70-160%.

Table 2 Comparison between actual and predicted road traffic volumes in Korea (Unit: vehicles/day, %)

Road		Section	Open Year	Three Years Later after Opening		
				Predicted	Actual	Error Ratio
Public Sector	Seoul Outer Ring	Pangyo-Anhyun	2000	114,981	147,933	−22,28
	Chungang Expressway	Seoandong-Jaechun	2000	10,652	15,005	−29,01
		Jaechun-Manjong	2001	17,901	20,085	−10,87
		Manjong-Chuncheon	2001	8,640	12,863	−32,83
	West Coast Expressway	Donggunsan-Daecheon	2000	36,216	41,252	−12,21
		Mokpo-Muan	2001	21,366	15,693	36,15
	Daejeon-Jinju Expressway	Muju-Sannae	2001	30,831	29,042	6,16

Table 2 Comparison between actual and predicted road traffic volumes in Korea (Unit: vehicles/day, %) (continuation)

Road		Section	Open Year	Three Years Later after Opening		
				Predicted	Actual	Error Ratio
Public Sector	Middle Inland Expressway	Yeoju-Chungju	2002	38,179	34,145	11,81
		Kimcheon-Sangju	2001	32,106	118,004	−72,79
	Daegu-Pohang Expressway	Dodong-Chungtongwachon	2004	42,852	22,320	91,99
Private Sector	Cheonan-Nonsan Expressway	Cheonan-Nonsan	2003	53,692	29,988	79,04
	Buman Expressway	Bumyul-Yulha	2002	60,953	19,530	212,10
	Incheon Airport Expressway	Incheon-Goyang	2001	146,554	59,780	145,16

Note: The actual traffic volume on the Daegu-Pohang Expressway was observed two years after its opening.

In Korea, the credibility of traffic demand forecasts is also considered one of the most controversial issues, as several high-cost highways have become operational in recent years. In many cases, the actual traffic volumes are much lower than those predicted at the planning stage, as listed in Tab. 2. In only one among 13 cases, the discrepancy was within ±10%, while in five cases the traffic forecasting errors were > ±50%. These statistics demonstrate that errors and biases in traffic demand forecasts may increase significant risks in planning and financing road projects.

Standard & Poor's Rating Services (2003) found causes of failure in forecasting traffic volumes (listed in Tab. 3) and suggested that the development of a probabilistic model using MCS may improve the accuracy of forecasts. In this study, the uncertainties were emphasized to be mainly caused by external variables, which cannot be estimated by the traffic modeler.

Table 3 Causes of errors in forecasting traffic demand

From the 2002 study	Additional drivers identified in the 2003 study update
High toll tariffs and a miscalculation of willingness of the users to pay	Complexity of the transaction
Recession/economic downturn	Underestimation of the severity and duration of ramp-up
Failed future land use scenarios	Underestimation of the value of time (VOT)
Lower than expected time savings	Use of a single, average VOT rather than a distribution of VOT
Improvements to competitive (toll-free) routes	Sensitivity of longer-term traffic forecasts to macroeconomic predictions, such as assumption about GDP growth
Considerably lower usage by trucks	
Lower off-peak/weekend traffic	

2 LITERATURE REVIEW

The author analyzed several studies related to traffic forecasts and decision-making. Several methodologies and cases suggest considering biases when interpreting the results of statistical analysis of the inaccuracy of traffic forecasts (Flyvbjerg, 2005). The problem of over-forecasting demand in railway projects was assessed. The causes of forecast inaccuracy were categorized into railways and roads, and a solution was proposed (Flyvbjerg et al., 2005). A model based on real-time applications was proposed to analyze essential matters such as vehicle routing (Sarp et al., 2022). A decision-support platform was proposed to help planners understand the relationship between volume and cost related to transportation and find solutions in a short time (Serbanand Carp, 2021). The ramp-up phenomenon was formalized. In this phenomenon, the actual traffic volume is less than or overestimated than the predicted traffic volume. The cause of this phenomenon on an actual highway and method of approach to analyze the phenomenon were investigated. The negative impact on business decisions due to inadequate risk management was analyzed and reviewed in failure cases (Chung et al., 2006).

3 RESEARCH METHODOLOGY

The MCS-based approach proposed in this study was developed in three steps. First, the key factors causing errors and biases in traffic demand forecasts were identified based on a comprehensive review of traffic forecasting practices. Second, the effects of each variable on traffic volumes were quantified using MCS. Lastly, a statistical approach was constructed to provide an interval estimation of traffic volumes based on the findings of MCS.

Table 4 MCS applications to transportation project appraisal

Researcher	Objective	Projects	Methodology and Contents
Louis Y. Pouliquen (1972)	Supplementary economic analysis for IBRD projects in underdeveloped countries	Construction project of Lighterage harbor in Mogadiscio, Somalia (1967)	Estimation of the probability density function of costs and the cumulative density function of IRR using MCS
IBRD (1972)	Introduction of the stochastic analysis to IBRD projects for underdeveloped countries	Construction of 965 mile two lane road in Zambia (Copper bel-Dares-Salaam harbor)	Estimation of the probability density function of costs and the cumulative density function of IRR using MCS
Touran (1997)	Integrated analysis of risks in financing and construction of FTA rail projects in the U.S.	Analysis of construction cost and cash flow for 19.3 km rail project by the U.S.	Analysis of financial risk with regard to funding resources using MCS
Inho Kim, Changtak Hyun et al. (2000)	Risk analysis model for private sector light rail projects	Case study on the build-transfer-operation private investments for mid-sized city light rail	Estimation of the probability density function of costs/benefits and cumulative density function of NPV using MCS
Darrin et al. (2000)	Construction of risk analysis model for private sector projects	Sewage control (East Scotland AV&S project)	Estimation of the cumulative density function of IRR using MCS

Source: Korea Transport Institute, Demand Forecasting Errors in Road Projects: Causes and Effects, 2007.

MCS, a scheme employing random numbers, is widely used to solve analytically intractable problems in statistics. MCS-based computations are simpler than other mathematical algorithms. Also, MCS is suitable for practical engineering problems with no exact solutions. Thus, MCS has been adopted in many areas, including the evaluation of large-scale infrastructure investment decisions, as listed in Tab. 4.

To increase the efficiency of MCS, identifying the most critical variables that influence the uncertainties in traffic demand forecasts is necessary. Then, the probability distribution of each key variable needs to be constructed accordingly. If a probability distribution cannot be defined in a specific functional form, an empirical distribution can be used. In this study, the variables associated with the error and bias in traffic demand forecasts were assumed to be independent of each other; therefore, the joint probability between two or more variables was not considered. Fig. 1 illustrates the five-step process to estimate the range of traffic volumes based on the variables associated with the forecasting error and bias.

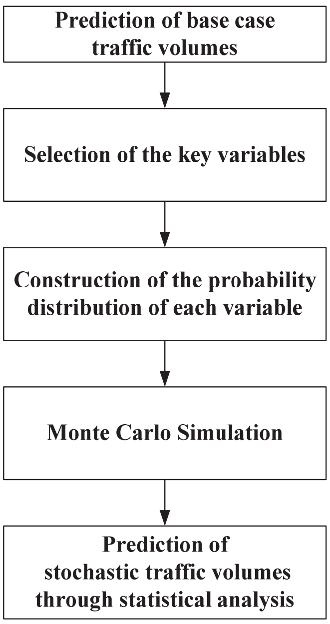


Figure 1 Flowchart of the MCS-based approach

Table 5 Applications of probability distribution to risk variables

Distribution	Application Conditions	Literature
Uniform	.Insufficient data .Relatively small fluctuations in data .Difficult to use the maximum likelihood estimators	.Spooner (1974) .Touran, Bolster (1994)
Triangular	.Reliable to use the maximum likelihood estimators .Reliable information about the maximum and minimum values	.Maker, Bryant (1990) .Spooner (1974) .Touran, Bolster (1994)
Normal	.Possible to use the maximum likelihood estimators	.Bodie (1993)
Beta	.Unimodal .Skewed pattern	.Touran (1987) .Spooner (1974) .Touran, Bolster (1994)
Log Normal	.Unimodal .Skewed pattern .Commonly-used function for civil and electric infrastructure costs	.Touran (1987) .Teichoz (1964), .O'Shea (1966) .Gaarslev (1969)

4 RESULTS AND DISCUSSION

4.1 Probability Distribution of the Value of Time

According to the previous studies, the uncertainty in the value of time (VOT) perceived by road users is a key determinant affecting the error and bias in traffic forecasting (Standard & Poor's Rating Services, 2003; Chung and Chang, 2007; Flyvbjerg, 2005; Flyvbjerg, 2006). Therefore, VOT was selected as a key variable in this study to apply the proposed approach to estimate the risk in traffic demand forecasts using actual survey data. The user-equilibrium traffic assignment assumes that users should rationally choose the minimum-cost route. The route cost changes according to VOT perceived by road users. The following generalized travel cost function was used in this study:

$$T = T_0 \cdot \left[1 + \alpha \cdot \left({}^{V}\!/_{C} \right)^{\beta} \right] + D \cdot \omega \qquad (1)$$

where: T - link travel time; T_0 - free flow link travel time (min); V - link volume (pcu/h); C - link capacity (pcu/h); α, β - parameters; D - link distance (km); ω - weighted value along link distance for expressway (h/km)

In the case of toll roads, the weights were determined by vehicle type, considering the user VOT. Thus, the variability in VOT was determined by the changes in link traffic volumes. As described in Tab. 6 and Fig. 2, VOT varies as the labor market and income level change. Since 2000, for business travelers, the VOT growth rate has been 4.99% per year, and the variance of VOT also has increased. Therefore, VOT can be modeled as a random variable using the statistical patterns observed from historical and census data, as indicated by the data randomness (A) and time gap (B) in Fig. 2.

Table 6 The labor market and income level change

Year	Current Market Price		Year 2000 Constant Market Price		Consumer Price Index
	Mean	Deviation	Mean	Deviation	
2000	6,373	1,433	6,373	1,433	84,9
2001	6,866	1,566	6,601	1,506	88,3
2002	7,693	1,757	7,193	1,643	90,8
2003	8,286	1,987	7,492	1,797	93,9
2004	8,450	1,963	7,373	1,713	97,3
2005	9,482	2,222	8,050	1,887	100,0
2006	10,276	2,342	8,536	1,945	102,2

Source: http://laborstat.molab.go.kr/

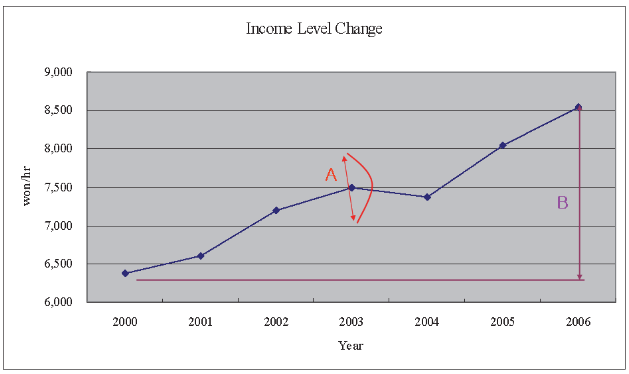


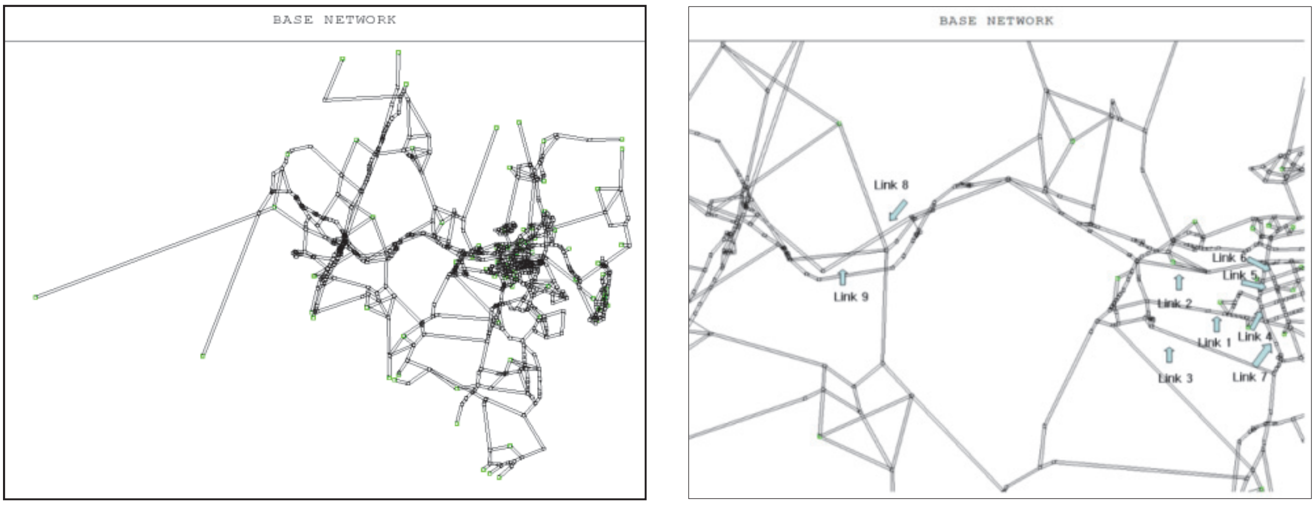
Figure 2 Income level change

Table 7 Distribution of monthly incomes (Unit: KRW)

Index	Classification	Percentage
1	~500,000	4,46
2	500,000-1000,000	7,13
3	1000,000-1500,000	9,6
4	1500,000-2000,000	11,68
5	2000,000-1500,000	12,76
6	2500,000-3000,000	11,62
7	3000,000-3500,000	10,32
8	3500,000-4000,000	8,01
9	4000,000-4500,000	6,21
10	4500,000–5000,000	4,56
11	5000,000–5500,000	3.56
12	5500,000–6000,000	2.37
13	6000,000~	7.7

Source: http://www.kosis.kr/

VOT of a person can be reasonably assumed to be related to their income; therefore, the probability distribution of VOT can be derived from that of income. The income statistics in 2006, summarized in Tab. 7, indicate a normal-like distribution. Thus, a normal distribution was used to model the variability in VOT perceived by users. Based on the "Guidelines for the Preliminary Feasibility Study (Korea Development Institute, 2004)", the average VOT of a business traveler is assumed to be KRW (Korean Won) 13,257/person-h. Its standard deviation is estimated to be KRW 1,782/person-h using "National Labour Statistics (Ministry of Labour, 2003)", such as monthly incomes, working hours, and number of workers by job.



(a) Road network (b) Study links

Figure 3 Test network

4.2 Experiment

The origin-destination (O-D) tables and traffic networks used in this study were developed using the Korea Transport Database. The base-year model was developed for the year 2006. Fig. 3 illustrates the network used in this study and nine road links selected for traffic forecast risk assessment. The test network is a real-world road network located in the city of Ulsan, which has the largest chemical and heavy-industrial complex in Korea. The additional link travel delay due to the toll was calculated using the toll structure and VOT. The toll impedance was modeled as a weight on the road link, and the volume-delay function (VDF) was used to calculate the link travel cost. The averages of additional weights for two, four-, and more than six-lane toll road links are 0,102, 0,205 and 0,246 min/km, respectively. Their standard deviations are 0,0209, 0,0417, and 0,050, respectively.

Fig. 4 shows the process of estimating the range of traffic volumes according to the variability in VOT. In this experiment, the effect of the VOT change was assumed to be reflected only in traffic assignment. Hence, every traffic assignment was assigned a different VOT, which was randomly determined through MCS using the mean and variance of the VOT distribution. The results of each traffic assignment were stored until the maximum number of assignments was reached. Then, the statistical analysis was performed to produce the stochastic traffic volumes for each road link. In this study, 1,000 traffic assignment simulation runs were iterated using EMME/2 (a commercialized transport demand modeler).

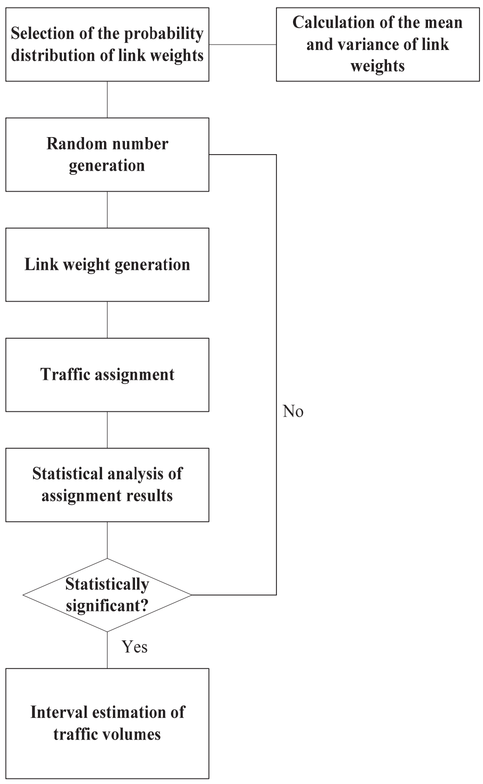


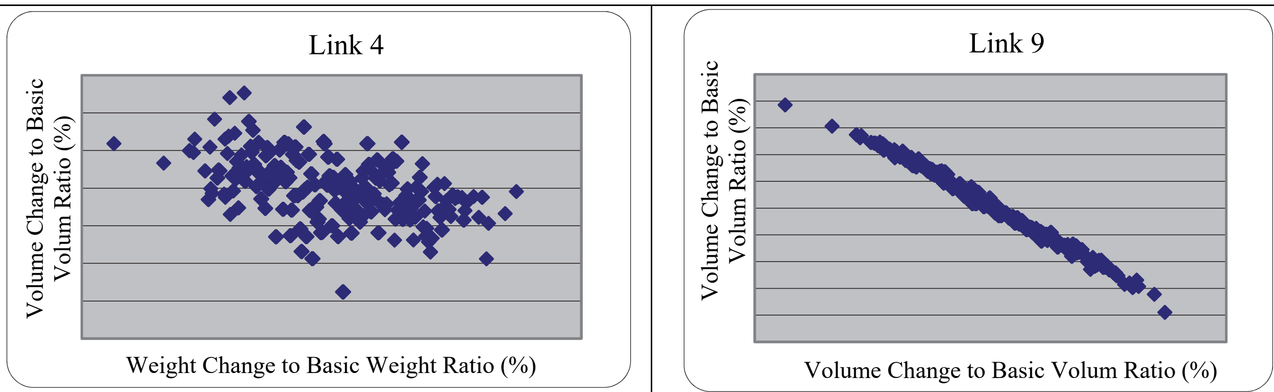
Figure 4 Process of estimating the range of traffic volumes

Table 8 Study links

Link Number	Road Classification	Toll	Length / km
1	Six-lane Municipal Road	No toll	1,95
2	Four-lane Municipal Road	No toll	2,3
3	Four-lane Municipal Road	No toll	4,32
4	Six-lane Municipal Road	No toll	0,48
5	Two-lane Municipal Road	No toll	0,54
6	Four-lane National Road	No toll	0,57
7	Six-lane National Road	No toll	0,78
8	Four-lane Expressway	Tolled	3,39
9	Four-lane Expressway	Tolled	3,39

4.3 Analysis Result

The MCS experiments suggested that in the case of road links connecting toll roads, VOT and traffic volumes were negativelycorrelated, as shown in Fig. 5. Thus, as VOT increased, the travel impedance on toll roads diminished and traffic volume increased. Hence, toll road links, such as links 8 and 9, showed a stronger negative correlation between VOT and traffic volume. Conversely, links 4 and 5 without toll did not show any significant correlation with VOT changes. The traffic volumes varied between −1% and 3% with the changes in VOT. The experiments also suggested that the probability distribution for link 4 can be a normal or logistic function, while a Weibull distribution should be used for link 6. The selected functions that are appropriate for the probability distribution of each link are summarized in Tab. 9.



(a) Link 4 (b) Link 9

Figure 5 Relationship between the traffic volume and VOT weight

Table 9 Goodness of fit of probability distributions for each study link

Good of Fitness Rank	Link 1	Link 2	Link 3	Link 4	Link 5	Link 6	Link 7	Link 8	Link 9	Total
1	Weibull	Pearson 6	Extreme Value	Lognormal	Weibull	Weibull	Beta	Erlang	Lognormal	Beta
2	Extreme Value	Inverse Gaussian	Lognormal	Normal	Extreme Value	Gamma	Triangular	Log-Logistic	Beta	Weibull
3	Logistic	Lognormal	Inverse Gaussian	Logistic	Logistic	Normal	Weibull	Lognormal	Normal	Erlang
4	Lognormal	Gamma	Pearson 6	Weibull	Lognormal	Lognormal	Erlang	Gamma	Weibull	Lognormal
5	Beta	Erlang	Erlang	Beta	Beta	Erlang	Gamma	Beta	Logistic	Gamma
6	Triangular	Beta	Gamma	Extreme Value	Triangular	Inverse Gaussian	Inverse Gaussian	Logisitc	Extreme Value	Inverse Gaussian
7	Uniform	Weibull	Weibull	Pearson 5	Uniform	Log-Logistic	Lognormal	Inverse Gaussian	Pearson 5	Normal
8	Normal	Extreme Value	Log-Logistic	Triangular	Normal	Logistic	Log-Logistic	Normal	Triangular	Log-Logistic
9	-	Log-Logistic	Exponential	Uniform	-	Beta	Exponential	Weibull	Uniform	Exponential
10	-	Exponential	Logistic	-	-	Exponential	Logisitc	Exponential	-	Logistic
11	-	Logistic	Normal	-	-	Pareto	Pareto	Pareto	-	Pareto
12	-	Normal	Pareto	-	-	Extreme Value	Extreme Value	Extreme Value	-	Extreme Value
13	-	Pareto	Beta	-	-	Pearson 6	Pearson 6	Pearson 6	-	Pearson 6
14	-	Triangular	Triangular	-	-	Triangular	Normal	Triangular	-	Triangular
15	-	Uniform	Uniform	-	-	Uniform	Uniform	Uniform	-	Uniform
Accept	All reject	All reject	All reject	Normal Logistic	All reject	Weibull	All reject	All reject	Lognormal Beta Normal	All reject

Table 10 Result of the traffic volume statistic

Classification	Link 1	Link 2	Link 3	Link 4	Link 5	Link 6	Link 7	Link 8	Link 9	Sum
Basic Forecast	55,838	6,429	15,297	25,797	11,354	31,092	31,360	42,263	34,843	254,273
Mean	56,050	6,622	15,198	26,286	11,306	31,071	32,025	41,574	34,930	255,061
Deviation	243	186	547	401	221	102	725	804	757	2,921

Since links 4 and 9 followed normal distributions (Table 9), the following equation was used to estimate stochastic traffic volumes with a 95% confidence interval:

$$m-1.96\times\sigma\sqrt{1+\frac{1}{n}}\leq x\leq m+1.96\times\sigma\sqrt{1+\frac{1}{n}} \quad (2)$$

where: m - mean; σ - standard deviation; n - number of samples; x - traffic volume.

As listed in Tab. 11, with a 95% confidence interval, the traffic volumes on links 4 and 9 increased from 25,499 (pcu/day) to 27,073 (pcu/day) and from 33,466 (pcu/day) to 36,414 (pcu/day), respectively.

Table 11 Results of the stochastic traffic volume with a 95% confidence interval

Classification		Link 4	Link 9
Basic Forecast		26,286	34,930
95% Confidence Interval	From	25,499	33,446
	To	27,073	36,414

5 CONCLUSION

Traffic demand forecasts are essential for the assessment of transportation project feasibility. However, the significant discrepancy between the actual and predicted traffic volumes has raised controversial issues about the credibility and risk of traffic demand models. Several researchers have attempted to quantify the error and bias in traffic demand forecasts; however, no methodological framework that can be seamlessly applied to real-world traffic demand forecasting practices has been obtained.

In this study, an MCS-based approach was proposed to provide stochastic traffic volumes, considering key variables associated with the error and bias in traffic demand forecasts. A systematic framework was developed to practically estimate the magnitude of uncertainties associated with future traffic volumes. Key variables were identified through a comprehensive review and analysis of previous traffic forecasting practices in Korea. Experimental analysis was performed using VOT, which is considered to be one of the key variables affecting traffic forecasts. The probability distribution of VOT was determined using income-related statistics. These statistics assumed the VOT of a person to be closely correlated with their income. The experiments indicated the effectiveness of the MCS-based approach in predicting stochastic traffic volumes. The experimental findings also suggest that the proposed approach can be easily and flexibility adapted by traffic forecasting practitioners. The analysis results showed the ability of the proposed approach to clearly capture the change in link traffic volumes owing to the statistical variations in VOT. The experiments indicated that the uncertainties in VOT perceived by road users can be used to estimate the risks of toll road financing. The elasticity of traffic volume to VOT for each link can be derived from the MCS-based analysis implemented in this study. This analysis method can be used as a key input to the road project feasibility study.

This study introduced an alternative methodological perspective to address the stochastic traffic demand associated with the error and bias in traffic forecasts. The stochastic nature of future traffic volumes has several causes. In this study, despite the probable existence of several sources of the discrepancy, only VOT was assumed to explain the gaps between the actual and predicted traffic volumes. Hence, the study needs to be extended to consider other variables related to traffic flow modeling and future development-related discrepancies.

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