한국소음진동공학회논문집 제 14 권 제 4 호, pp. 276~286, 2004.

루이빌大 개별State-specific 데이터를 이용한 도로 교통소음 수준 비교 - 오픈공간에서 -

Comparing Highway Traffic Noise Emission Levels Using Individual UofL State-specific Data - Based on Open Space -

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(2003년 5월 29일 접수 : 2004년 3월 18일 심사완료)

Key Words : Coincidence (일치성), Highway (도로), Noise (소음), Parallelism (평행성), FHWA (미연방도로부), STAMINA (소음예측모형, 1982), and TNM (소음예측모형, 2002)

요 약

현재, 미 연방도로부에서는 도로교통소음분석을 위한 예측모형 (TNM & STAMINA)을 미 전 지역에 제공하고 있고, 이와 관련된 여러가지 연구논문들이 수행되고 있는바, 모델을 이용한 예측치와 실측치 간의 비교·분석 연구논문을 통하여 차이점이 존재하는 것을 증명하고 있다. 따라서 본 연구논문은 소음예측모형의 핵심자료로 사용될 수 있는 루이빌대(UofL) 회귀모형들을 차종별 (소형, 중형, 대형) 그리고 주별 (아리조나, 콜로라도, 조지아, 캔사스, 와싱톤)로 구분하여 그 차이점을 통계적으로 비교·분석·결론을 도출하였다. 그 결과 아리조나와 콜로라도 (중대형)를 제외한 나머지 개별 State-specific 데이터는 통계적으로 서로 다른 것으로 나타났다.

1. Introduction

Excessive highway noise levels continue to cause a serious pollution problem in urban areas throughout the United States. This unseen pollutant affects the lives of more than ninety million people, causing interference with sleep and communication, as well as a degradation in general quality of life(1). In particular, highway traffic noise has become a major problem in Asian countries as well as in the United States of America's urban highway environments. In response to this concern, the FHWA in the U.S. is committed to providing effective technology and solutions for dealing with the unwanted sound associated with highway traffic noise. The FHWA provides a continuing effort to improve engineering methods for the prediction of highway traffic noise.

In the early 1980s, the Standard Method In Noise Analysis (STAMINA)[2], version 2.0, was developed for the prediction of traffic noise and

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barrier design by the FHWA. STAMINA 2.0 also contains a component that performs optimization of barrier analysis and design (OPTIMA) and has been in use for almost two decades. Since that time, research by the FHWA and the Volpe National Transportation System Center (VNTSC)[3] has continued in the methodology and technology of noise prediction, barrier design, and computer software coding. The FHWA consequently identified the need to develop a method that utilizes the results of this research. In 1995, the FHWA and the VNTSC[3]issued a report detailing the results of a new national Reference Energy Mean Emission Level (REMEL) analysis. In May, 2002 the FHWA released the Traffic Noise Model (TNM)[4], version 2.0.6, which is the FHWA's new computer program for highway noise prediction and analysis.

The FHWA model (STAMINA & TNM) calculates a predicted sound level by adjusting a Reference Energy Mean Emission Level(REMEL) database, which is the empirical foundation of the prediction model. In addition, traffic flow, distance from the roadway, the effects of shielding, etc. are adjusted based on actual site characteristics. The FHWA model is mathematically stated as[2, 3]:

$$L_{eq}(h)_i = REMEL + traffic\ flow\ adjustment + distance\ adjustment + finite\ roadway\ adjustment + shielding\ adjustment \quad (1)$$

where, $Leq(h)_i$ the hourly equivalent sound level of the i^{th} classof vehicles.

The main database (REMELs) form the basis from which a traffic noise prediction model generates expected sound levels for all vehicles on the highway. The noise generated by vehicles is affected by various parameters, such as local environmental factors, pavement types and condition, vehicle types and sub-type, and speeds. Therefore, in order to obtain the most accurate results for highway traffic noise prediction, the REMEL data must accurately represent vehicle populations and operating conditions.

2. Literature Review

Numerous studies[5~9]have been performed to verify prediction model accuracy for the states of Georgia, California, Florida, Ontario in Canada, and Riyadh in Saudi Arabia, indicating that the national REMEL data inSTAMINA 2.0 either over-predicts or under-predicts noise levels by several decibels. Lately, the study by Harris et al.[10] demonstrated that a difference still exists between the most recent national traffic noise prediction model REMEL data and field measurements. Another study by Cohn et al.[11] was conducted to determine if the noise emission characteristics of Arizona state highway vehicles are consistent with the data obtained by the FHWA. This study found a statistical difference between the Arizona state-specific REMEL data and the VNTSC REMEL data.

This research effort will focus on determining if there is a statistically significant difference between individual UofL state data sets.

3. Methodology

3.1 Data Measurements

The FHWA model predicts sound levels through several adjustments to the prediction model, such as traffic characteristics, topography, and characteristics of roadways. Of particular interest in this study is the Reference Energy Mean Emission Level (REMEL), which forms the basis of the FHWA model. Therefore, the first step in the FHWA prediction procedure was the determination of the REMEL curves based on the following vehicle types: automobiles, medium trucks, and heavy trucks. These vehicle types are defined as [3]

- Automobiles: All vehicles with two axles and four tires, designed primarily to carry nine or fewer passengers or light cargo. Gross vehicle weight is less than 4,480 kg.
- Medium Trucks: All cargo vehicles with two axles and six tires. Gross vehicle weight is between 4,480 and 11,945 kg.
- Heavy Trucks: All cargo vehicles with three or more axles. Gross vehicle weight is greater than 11,945 kg.

The REMEL data points are measured at a reference distance of 15 meters perpendicular from the centerline of the roadway, with the microphone height placed at 1.5 meters above pavement elevation, and using the A-weighted maximum pass-by sound levels measured for individual vehicles. All measurements of the UofL Research Foundation Team were conducted in accordance with FHWA Report No. FHWA-PD-96-046, Measurement of Highway Related Noise.[12]

3.2 Data Comparison

A statistical method was designed to test the coincidence and parallelism of regression curves for data sets representing different states. In fact, the REMEL curves aredeveloped based on the data sets, which are the main database for the noise prediction model. The comparison results are also confirmed visually by examining the results using a graphical approach. The methodology (a single multiple regression line which combines two simple regression lines using a dummy variable) chosen for this comparison of two simple regression lines is a powerful approach yielding accurate results. Furthermore, Drs. Kleinbaum and Kupper, professors at the University of North Carolina, suggest, "a preferred way to test the coincident lines is to employ a multiple regression model involving dummy variables."[13] Therefore, this method was selected for this comparison study.

This method compares both parallelism and the intercept (i.e., test for coincidence) simultaneously by use of a single multiple regression line. If a test for coincidence is statistically the same, it can be asserted that the regression lines are statistically the same. Otherwise, they are different.

A single multiple regression model, which combined two simple linear regression lines was used. The model included a dummy variable to distinguish between the data groups. The simple regression line for the "State A" data set is Eq. 2, and a simple regression line for a "State B"data set is Eq. 3 [13]

$$(L_0)_{State\ A(i)} = C_A + D_A LOG_{10}(S) \quad (2)$$

$$(L_0)_{State\ B(i)} = C_B + D_B LOG_{10}(S) \quad (3)$$

where $(L_0)_{State\ A(i)}$ and $(L_0)_{State\ B(i)}$ represent the maximum sound levels of ith class of vehicles and takes the form of State "A" and State "B" simple linear regression lines as a function of LOG_{10} speed. C_A and C_B (the intercepts) and D_A and D_B (the slopes) are constants, and S is the speed in kilometers per hour.

These two models[13] are combined into a single multiple regression model using a dummy variable (0 or 1) represented in Eq. 4 as Z(usually values like 0 or 1, which simply describes no meaningful measurement level of the variable but rather act only to indicate the categories of interest represented in Eq. 4) as Z (Kleinbaum and Kupper, 1989).

$$(L_0)_{State\ A(i)} + (L_0)_{State\ B(i)} = C_A + D_A LOG_{10}(S) + C_B \cdot Z + D_B \cdot LOG_{10}(S) \cdot Z \quad (4)$$

where,

C_A, C_B	constant (intercept)
D_A, D_B	constant (slope)
Z	0 or 1 (a dummy variable)
S	speed, kph

If $Z=0$, then it represents the "State A" data, and if $Z=1$, then it represents the "State B" data.

The statistical analysis for this study consists of a two-step test for the presence of coincidence and parallelism in a single multiple regression model which contains the UofL individual state regression lines. This method begins by comparing the slopes and intercepts simultaneously of the two regression lines (test for coincidence). The null hypothesis (H_0) indicates that the two regression lines have the same slopes and intercepts (i.e., coincidence). The alternative hypothesis (H_1) indicates that the two regression lines have different slopes or different intercepts (i.e., non coincidence). Based on these concepts, all the statistical analysis procedures and scatter plotting in this paper were carriedout using both the Statistical Package for the Social Science, version 11.5 for Windows (SPSS 11.5 for Windows)[14] and Microsoft Excel in MS Office 2000.[15]

3.3 Comparison Possibilities

(1) Test of Coincidence

Coincidence between two regression lines means that they have the same slopes and intercepts. Therefore, the two simple regression lines consistently agree with each other over all speeds if they are coincident. For example,if a comparison of the "State A" data set to the State "B" data set shows that they are statistically coincident, then the two regression lines predict the same emission levels over all speeds. On the other hand, if the statistical test comparing them is significant, it can be concluded that they are statistically not coincident.

(2) Test of Parallelism

In the case of parallelism, two simple regression lines have the same slope in common, but they have different intercepts. This implies that the two regression lines are parallel but non coincident, indicating that the two regression lines are different. This case illustrates that one regression curve has consistently predicted higher (or lower) emission levels than the other regression curve over all speed ranges.

4. Analysis of Data Sets

The purpose of this study is to determine if statistically significant differences exist among the five different University of Louisville (UofL) state data sets. The analysis was performed by use of a single multiple regression model, which determined slopes and intercepts simultaneously, using a dummy variable. The data sets were also examined graphically by the regression curves based on data points. The regression curves (i.e., the individual UofL state data regression curves) developed by the regression analyses were compared by the differences between their *p-values* (a 95 percent confidence level) from SPSS[14] calculations

4.1 Comparison parameters

This research used the UofL REMEL data by the field measurements of the University of Louisville Research Foundation Team in

Table 1 A summary of automobile, medium trucks, and heavy truck data measurements obtained by UofL

Vehicle Class	AZ	CO	GA	KS	WA
Auto	526[1]	722	544	864	1,011
	(39-113)[2]	(32-113)	(32-113)	(43-67)	(32-113)
MT	486	270	448	427	508
	(39-113)	(32-113)	(42-113)	(43-67)	(32-113)
HT	495	403	494	422	522
	(32-113)	(35-113)	(32-113)	(43-68)	(32-113)

[1] Number of data points, [2] speed, kphcollected

Arizona(AZ), Colorado (CO), Kansas (KS), Georgia (GA), and Washington (WA). The data sets were grouped into three acoustically significant types: automobiles, medium trucks, and heavy trucks.

Table 1 presents a summary of the total number of measurement events at speeds ranging from 32 to 113 kph used in this study. The total number of data points collected by UofL for automobiles is 526 in AZ, 722 in CO, 544 in GA, 864 in KS, and 1,011 in WA at speed ranges from 32 to 113 kph.

In addition, the number of data points for medium trucks is 486 in AZ, 270 in CO, 448 in GA, 427 in KS, and 508 in WA at speed ranges from 32 to 113 kph. Finally, the number of data points for heavy trucks is 495 in AZ, 403 in CO, 494 in GA, 422 in KS, and 522 in WA at speed ranges from 32 to 113 kph

4.2 Automobiles

An examination of Table 2 illustrates the results from a comparison among the UofL data sets at speeds ranging from 32 to 113 kph for automobiles. In addition, if the calculated *p-value* for the coincidence test is greater than 0.05, the two regression curves are considered to be statistically the same with a 95% confidence level. Conversely, if the calculated *p-value* for the coincidence test is less than 0.05, the two regression lines are considered to be statistically different. The same methodology (i.e., calculated p-value) employed for the coincidence test was applied to the parallel test.

As shown in Table 2, the comparison results demonstrate that analysis of the individual UofL data sets indicates different regression lines, meaning that they have either unequal slopes or unequal intercepts over the entire range of speed for automobiles,as shown by Figs. 1 through 10 in the Appendix. A further examination of Table 2 indicates that the comparison results of the

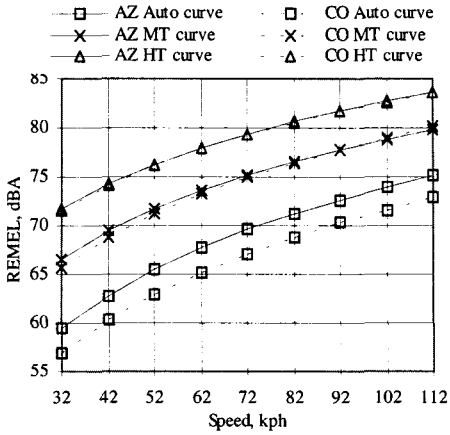

Fig. 1 AZ versus CO REMELs for auto, medium, and heavy

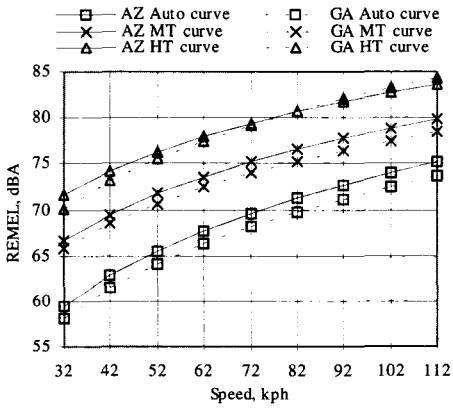

Fig. 2 AZ versus GA REMELs for auto, medium, and heavy

Table 2 Results of the comparison of the individual UofL data sets for automobiles

Analysis Results		*p-value*				
		AZ	CO	GA	KS	WA
AZ	Coincidence	1.000	0.000	0.000	0.000	0.000
	Parallelism	-	0.726	0.804	0.000	0.001
CO	Coincidence		1.000	0.000	0.000	0.000
	Parallelism		-	0.608	0.000	0.002
GA	Coincidence			1.000	0.000	0.000
	Parallelism			-	0.000	0.003
KS	Coincidence				1.000	0.000
	Parallelism				-	0.000
WA	Coincidence					1.000
	Parallelism					-

analysis of the AZ data set and the CO and GA data sets demonstrate statistically parallel regression lines (*p-value*: 0.726 and 0.804 is greater than 0.05 for parallelism test between the AZ data set and the CO as well as GA data sets in Table 2), which means that they share common slopes but unequal intercepts over all speeds. That is, the AZ regression curve lies consistently above the CO and GA regression curves over all speeds, as shown by Figs. 1 and 2 in the Appendix (In Table 3, the differences between the AZ regression curve and the CO curve are 2.6 to 2.3 dBA at all speeds).

In addition, the CO regression curve lies completely below the GA regression curve over all speeds, as reflected by Fig. 5 in the Appendix.

The AZ regression curve is absolutely intersected by the regression curves of KS and WA, as pictured by Figs. 3 and 4 in the Appendix, indicating that they have unequal slopes and unequal intercepts over all speeds. Furthermore, the AZ, CO, GA, KS, and WA regression curves calculate an emission level of 74.0 dBA, 71.6 dBA, 72.5 dBA, 75.3 dBA, and 74.1 dBA, respectively, at speeds of 102 kph.

Table 3 illustrates the differences among the UofL individual state regression curves at speeds ranging from 32 to 113 kph. The differences in the emission levels of the AZ regression curve compared to those of the CO, GA, KS, and WA curves are 2.6 to 2.3 dBA, 1.3 to 1.5 dBA, 4.0 to -1.8 dBA, and 1.9 to -0.3 dBA, at speeds ranging from 32 to 113 kph, respectively.

In addition, the differences of the CO regression curve compared to those of the GA, KS, and WA curves are -1.3 to -0.8 dBA, 1.4 to -4.1 dBA, and -0.8 to -2.6 dBA, at speeds ranging from 32 to 113 kph, respectively.

4.3 Medium Trucks

Table 4 illustrates the results from a comparison among the UofL individual state data sets for medium trucks. The AZ regression curve is statistically the same as the CO regression curve, and the KS regression curve is statistically the same as the WA regression curve, as shown by Figs. 1 and 10 in the Appendix. In other words, except for the AZ-CO comparison and KS-WA comparison, all the other state data sets differ from each other, implying that they have either unequal slopes or unequalintercepts over the entire range of speed for medium trucks. Figs. 2 through 9 in the Appendix are provided to visually confirm the statistical testing results.

A further examination of Table 4 exhibits that the comparison between the AZ data set and the

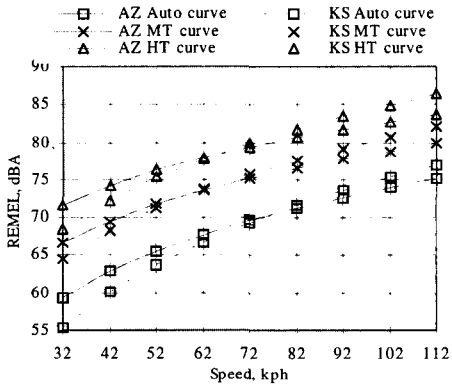

Fig. 3 AZ versus KS REMELs for auto, medium, and heavy

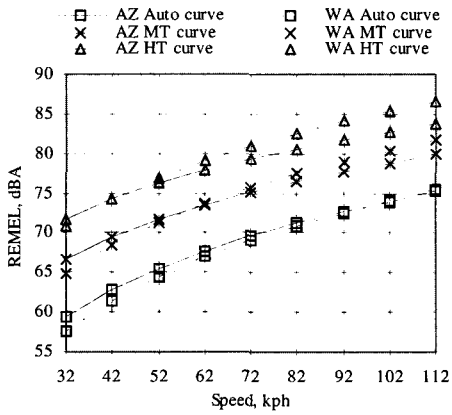

Fig. 4 AZ versus WA REMELs for auto, medium, and heavy

GA data setindicates parallel regression curves, meaning that they have statistically equal slopes but unequal intercepts over all speeds, as reflected by Fig. 2 in the Appendix. For example, the AZ curve lies completely above the GA regression curve over all speeds, as shown in Fig. 2 in the Appendix.

For medium trucks, the AZ, CO, GA, KS, and WA regression curves calculate emission levels of 78.8 dBA, 78.9 dBA, 77.5 dBA, 80.6 dBA, and 80.4 dBA, respectively, at speeds of 102 kph. However, the AZ curve yields 66.6 dBA, while the CO, GA, KS, and WA curves yield 65.6 dBA, 65.7 dBA, 64.5 dBA, and 64.8 dBA, respectively, at a speed of 32 kph.

Additionally, Table 5 illustrates the differences among the UofL individual state regression curves at speeds ranging from 32 to 113 kph. The differences in the emission levels of the AZ regression curve compared to those of the CO are 1.0 to -0.2 dBA, at speeds ranging from 32 to 113 kph. In addition, the differences in the emission levels of the KS regression curve compared to those of the WA are -0.3 to 0.3 dBA, at speeds

Table 3 Differences in emission levels (dBA) between the individual UofL data sets for automobiles

Model Comparison	Speed, kph								
	32	42	52	62	72	82	92	102	113
AZ - CO	2.6	2.6	2.5	2.5	2.4	2.4	2.4	2.4	2.3
AZ - GA	1.3	1.3	1.4	1.4	1.4	1.4	1.5	1.5	1.5
AZ - KS	4.0	2.8	1.8	1.0	0.3	-0.3	-0.9	-1.3	-1.8
AZ - WA	1.9	1.4	1.0	0.7	0.5	0.3	0.1	-0.1	-0.3
CO - GA	-1.3	-1.2	-1.1	-1.1	-1.0	-1.0	-0.9	-0.9	-0.8
CO - KS	1.4	0.2	-0.7	-1.5	-2.2	-2.7	-3.2	-3.7	-4.1
CO - WA	-0.8	-1.2	-1.5	-1.7	-2.0	-2.2	-2.3	-2.5	-2.6
GA - KS	2.7	1.4	0.4	-0.4	-1.1	-1.8	-2.3	-2.8	-3.3
GA - WA	0.5	0.0	-0.3	-0.7	-0.9	-1.2	-1.4	-1.6	-1.8
KS - WA	-2.2	-1.4	-0.8	-0.2	0.2	0.6	0.9	1.2	1.5

Table 4 Results of the comparison of the individual UofL data sets for medium trucks

Analysis Results		*p-value*				
		AZ	CO	GA	KS	WA
AZ	Coincidence	1.000	0.552	0.000	0.000	0.000
	Parallelism	-	-	0.586	0.000	0.000
CO	Coincidence		1.000	0.000	0.001	0.000
	Parallelism		-	0.183	0.039	0.035
GA	Coincidence			1.000	0.000	0.000
	Parallelism			-	0.000	0.000
KS	Coincidence				1.000	0.802
	Parallelism				-	-
WA	Coincidence					1.000
	Parallelism					-

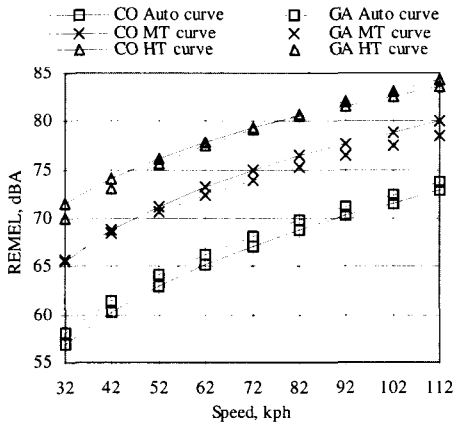

Fig. 5 CO versus GA REMELs for auto, medium, and heavy

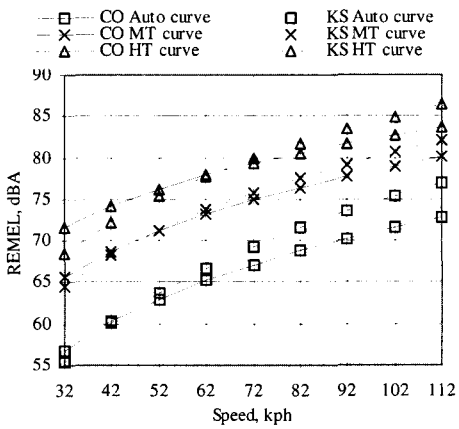

Fig. 6 CO versus KS REMELs for auto, medium, and heavy

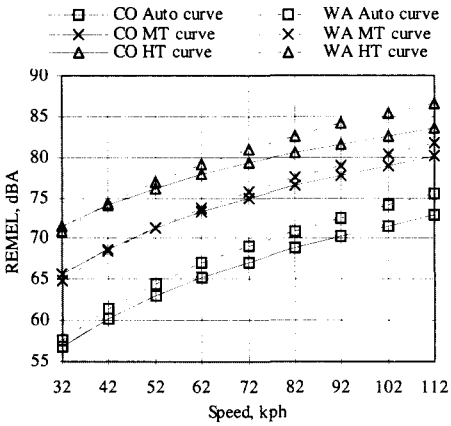

Fig. 7 CO versus WA REMELs for auto, medium, and heavy

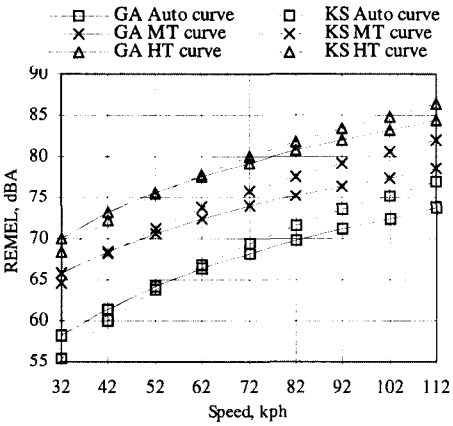

Fig. 8 GA versus KS REMELs for auto, medium, and heavy

Table 5 Differences in emission levels (dBA) between the individual UofL data sets for medium trucks

Model	Speed, kph								
Comparison	32	42	52	62	72	82	92	102	113
AZ - CO	1.0	0.7	0.5	0.4	0.2	0.1	0.0	-0.1	-0.2
AZ - GA	0.9	1.0	1.1	1.1	1.2	1.3	1.3	1.3	1.4
AZ - KS	2.1	1.2	0.5	-0.1	-0.6	-1.1	-1.5	-1.8	-2.2
AZ - WA	1.8	1.0	0.4	-0.1	-0.5	-0.9	-1.3	-1.6	-1.9
CO - GA	-0.1	0.3	0.5	0.8	1.0	1.2	1.3	1.4	1.6
CO - KS	1.1	0.4	-0.1	-0.5	-0.9	-1.2	-1.5	-1.7	-2.0
CO - WA	0.8	0.3	-0.1	-0.5	-0.8	-1.0	-1.3	-1.5	-1.7
GA - KS	1.2	0.2	-0.6	-1.3	-1.8	-2.3	-2.8	-3.2	-3.5
GA - WA	0.9	0.0	-0.7	-1.3	-1.8	-2.2	-2.6	-2.9	-3.2
KS - WA	-0.3	-0.2	-0.1	0.0	0.1	0.1	0.2	0.3	0.3

ranging from 32 to 113 kph.

A further examination of Table 5 illustrates the differences in the emission levels of the AZ regression curve compared to those of the GA, KS, and WA curves are 0.9 to 1.4 dBA (i.e., Parallelism between the AZ curve and GA curve), 2.1 to -2.2 dBA, and 1.8 to -1.9 dBA at speeds ranging from 32 to 113 kph.

The differences of the GA curve compared to those of the KS curve are 1.2 to -3.5 dBA at the entire range of speeds.

4.4 Heavy Trucks

Table 6 demonstrates the results from a comparison among the UofL individual state data sets for heavy trucks. Only the AZ regression curve is statistically the same as the CO regression curve in Table 6, as shownby Fig. 1 in the Appendix. In other words, except for the AZ-CO comparison, all the other state data sets differ from each other. This implies that they have either unequal slopes or unequal intercepts over the entire range of speed for heavy trucks. Figs. 2 through 10, in the Appendix, are provided to visually confirm the statistical testing results.

For heavy trucks, the AZ, CO, GA, KS, and WA regression curves calculate emission levels of 82.7 dBA, 82.6 dBA, 83.2 dBA, 84.9 dBA, and 85.4

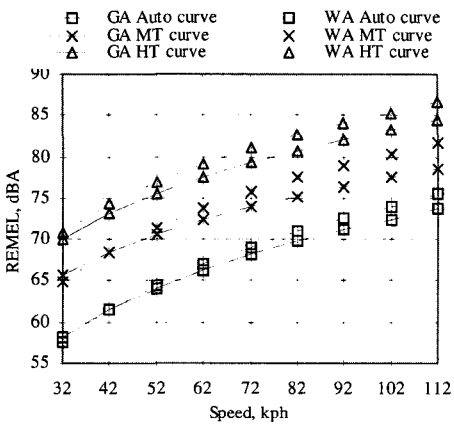

Fig. 9 GA versus WA REMELs for auto, medium, and heavy

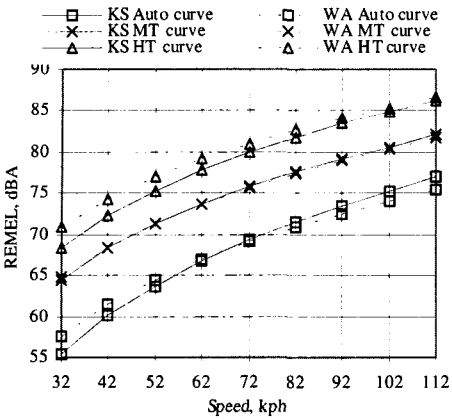

Fig. 10 KS versus WA REMELs for auto, medium, and heavy

Table 6 Results of the comparison of the individual UofL data sets for heavy trucks

Analysis Results		*p-value*				
		AZ	CO	GA	KS	WA
AZ	Coincidence	1.000	0.892	0.002	0.000	0.000
	Parallelism	-	-	0.001	0.000	0.000
CO	Coincidence		1.000	0.019	0.000	0.000
	Parallelism		-	0.008	0.000	0.000
GA	Coincidence			1.000	0.000	0.000
	Parallelism			-	0.000	0.035
KS	Coincidence				1.000	0.000
	Parallelism				-	0.003
WA	Coincidence					1.000
	Parallelism					-

Table 7 Differences in emission levels (dBA) between the individual UofL data sets for heavy trucks

Model	Speed, kph								
Comparison	32	42	52	62	72	82	92	102	113
AZ - CO	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
AZ - GA	1.6	1.1	0.8	0.4	0.2	-0.1	-0.3	-0.5	-0.7
AZ - KS	3.3	2.0	1.0	0.2	-0.5	-1.2	-1.7	-2.2	-2.7
AZ - WA	0.8	0.0	-0.7	-1.2	-1.6	-2.0	-2.3	-2.6	-2.9
CO - GA	1.5	1.0	0.7	0.3	0.1	-0.2	-0.4	-0.6	-0.7
CO - KS	3.1	1.9	0.9	0.1	-0.6	-1.2	-1.8	-2.3	-2.7
CO - WA	0.6	-0.1	-0.8	-1.3	-1.7	-2.1	-2.4	-2.7	-3.0
GA - KS	1.6	0.8	0.2	-0.3	-0.7	-1.1	-1.4	-1.7	-2.0
GA - WA	-0.9	-1.2	-1.4	-1.6	-1.8	-1.9	-2.0	-2.2	-2.3
KS - WA	-2.5	-2.0	-1.6	-1.3	-1.1	-0.8	-0.6	-0.5	-0.3

For heavy trucks, the AZ, CO, GA, KS, and WA regression curves calculate emission levels of 82.7 dBA, 82.6 dBA, 83.2 dBA, 84.9 dBA, and 85.4 dBA, respectively, at speeds of 102 kph. However, the AZ curve yields 71.7 dBA, while the CO, GA, KS, and WA curves yield 71.5 dBA, 70.0 dBA, 68.4 dBA, and 70.9 dBA, at a speed of 32 kph, respectively.

Table 7 indicates the differences between the UofL individual state regression curves at speeds ranging from 32 to 113 kilometers per hour. The differences in the emission levels of the AZ regression curve compared to those of CO are exactly 0.1 dBA, at speeds ranging from 32 to 113 kph.

Further examination of Table 7 illustrates the differences in the emission levels of the CO regression curve compared to those of the GA, KS, and WA curves are 1.5 to -0.7 dBA, 3.1 to -2.7 dBA, and 0.6 to -3.0 dBA at speeds ranging from 32 to 113 kph. Additionally, the differences in the emission levels of the GA regression curve compared to those of the KS and WA curves are 1.6 to -2.0 dBA and -0.9 to -2.3 dBA, at speeds ranging from 32 to 113 kph, respectively.

5. Conclusion

The main goal of this study was to determine whether statistically significant differences exist among the individual UofL state data sets. The differences among the individual UofL state data sets persisted all through this research work. The reasons for these differences may not be clearly explained, and this research work makes no attempt to do so.

If it can be demonstrated that state-specific REMEL data is more accurate than the national REMEL data by even 1.0dBA, the cost saving potential is significant. The highway noise community agrees that a 1.0 dBA reduction in sound level requires 0.61 meters of barrier height. At an average cost of $65 m2, this would lead to

a savings of $65,000 per kilometer.

A comparison among the five UofL state curves was conducted for the automobile case. The comparison results are completely not coincident among all the UofL state curves. This means that 0.0 % (0 out of 10 comparisons) of the comparison results were coincident among all the UofL states. For the medium trucks like the automobile case, the comparison results also demonstrated that only 20.0 % (2 out of 10 comparisons) were statistically coincident among the five UofL state curves. Finally, for heavy trucks, the comparison results also illustrated that only 10.0 % (1 out of 10 comparisons) were statistically coincident between the UofL state curves.

Accordingly, this research work proved that the individual state data sets are completely different, and strongly demonstrated that state-specific REMEL data is essential to accurate model predictions.This implies that one may use the U.S. data set to estimate Korea highway traffic noise; however, one can not predict the Korea traffic noise levels accurately.

Based onthe comparison results, this study further supports the theory that state-specific or country-specific (for example, Korea) REMEL data may generate more accurate results in current noise prediction model than the U.S. averages in the same models. In addition, future studies may be needed cause (i.e., the condition of the road surface, vehicle, and measurement site and environmental factors) of so much variation among individual state data sets.

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