

Artificial neural network analysis of the relationship between road-traffic noise and air pollutants and urban form indicators

Phillip KIM¹; Hunjae RYU²; Jong June JEON³; Seo IL CHANG⁴; Nokil PARK⁵

¹ Department of Energy and Environmental System Engineering, University of Seoul, Korea

² Korea Educational Environments Protection Agency, Korea

³ Department of Statistics, University of Seoul, Korea

⁴ School of Environmental Engineering, University of Seoul, Korea

⁵ Atlanta Regional Commission, USA

ABSTRACT

Road-traffic noise and air pollutants have adverse effect to urban dweller's health and life quality. For management of the noise and air pollutants, noise and air pollution maps can be used to provide quantitative information of noise and air pollution exposure levels. In this study, the more efficient method of noise and air pollution mapping was developed statistically. Noise and air pollutants' exposure change by small-scaled alteration of urban planning can be predicted by the method. The relationship between road-traffic noise level and air pollutants and urban forms for roads, buildings and land-use was analyzed by artificial neural network analysis. The selected representative urban form indicators are road-related(traffic volume, speed), building-related(floor space index, ground space index), and land-use-related indicators. The artificial neural network model was optimized by adjusting the number of hidden nodes and layers. The 2/3 of data sets extracted from a region was used for the model development to select the model with the least prediction error. The selected model was applied to the remaining 1/3 of data sets for verification. The result from the artificial neural network model were compared with that from engineering model

Keywords: Artificial neural network, Road-traffic noise, Urban form indicators

1. INTRODUCTION

Noise and air pollutants that could adversely affect the life and health of urban habitants share road traffic as a common source. Roads are social infrastructures that is essential for the maintenance and development of society. Therefore, it is practically impossible to reduce noise and air pollutants due to reduction or elimination of roads. A noise map is created using the road-traffic noise prediction model which takes into account the noise level emitted from the road and the processes in which the noise is absorbed, reflected and diffracted in the propagation path. And air pollutants map is created using emission level of air pollutants and dispersion model. The management of road-traffic noise and air pollutants is based on using of noise map and air pollutants map.

But creating noise map and air pollutants map requires verification through in-situ measurement and using considerable computation resource in the calculation process. And it needs a lot of cost, time and manpower in the creation process. So, it is necessary to research how to estimate road-traffic noise level and air pollutants concentration in urban area with minimum cost, time and manpower. In

¹ rlavlflq154@uos.ac.kr

² pgryuno1@schoolkeepa.or.kr

³ jj.jeon@uos.ac.kr

⁴ schang@uos.ac.kr

⁵ npark@atlantaregional.org

this study, the basic research was carried out to estimate the road-traffic noise level and air pollutants concentration based on statistical method. Among various statistical methods, the artificial neural network method was used.

Kumar, et al.(2015) fitted an artificial neural network model based on measured road-traffic noise and road information(traffic volume, heavy vehicle ratio and traffic speed). Predicted road-traffic noise level of artificial neural network model is similar to measured road-traffic noise level than that of linear regression model.(1) Garg et al.(2015) predicted road-traffic noise level based on traffic volume by car types(car, two-wheelers, medium commercial vehicles, three-wheelers bus and trucks) and traffic speed by car types(light vehicle, heavy vehicle) with artificial neural network model. Leq and L10 were used as unit. The artificial neural network model showed higher explanatory power than multiple linear regression model.(2) In the study of comparing predicted road-traffic noise levels based on conventional road-traffic noise prediction(UK, Northern Europe, Italy and France) and artificial neural network model, the results of artificial neural network model were most similar to measured noise level.(3) In the above research cases, the artificial neural network models were created based on measured noise level and road information(Traffic volume, speed and etc.) at a certain point. As a result, predicted road-traffic noise levels by ANN model were similar to the measured road-traffic noise levels compared than the conventional road-traffic noise prediction and linear regression. However, it is difficult to predict the representative road-traffic noise level in urban area, because the model reflects geographical and topographical characteristics of the certain point. Ryu, et al.(2014) predicted road-traffic noise of urban area using statistical method. A system of grid cells was placed on the study area, and the representative values of road-traffic noise level and urban form indicators were calculated in each grid cell. And the relationship between road-traffic noise and urban form indicators was analyzed using spatial statistical analysis.(4) In the case of predicting air pollutants spatial distribution, artificial neural network model was created based on road information(Traffic volume, Heavy vehicle ratio) and meteorological information(temperature, wind speed, humidity and sun radiation). And the model predicted concentration of PM2.5 at various height of highway side.(5)

In this study, the relationships between urban form indicators and road-traffic noise, air pollutants were analyzed with artificial neural network model. And the critical urban form indicators that affect to road-traffic noise and air pollutant's occurrence were analyzed.

2. DATA ANALYSIS AND DEFINITION

2.1 Gridding study areas

Gwangju metropolitan city in Republic of Korea and Fulton county in Atlanta, USA were selected as study areas. Gwangju was chosen to analyze the relationship between road-traffic noise and urban form indicators, and Fulton was chosen to analyze the relationship between air pollutants and urban form indicators. Gwangju had total area of 501km² and population of 1.46 million as 2017 when the noise map was created. And Fulton had total area of 1380km² and population of 1 million as 2015 when the air pollutants map created. A system of 200m×200m grid cells is placed on the study areas. The number of valid grid cell of Gwangju and Fulton is 5,933 and 26,717, respectively. Figure 1 shows the example of Gwangju city's grid cell system application.



Figure 1 – Grid cell system application to Gwangju
(c) Google Maps / Digital Globe / SK telecom

2.2 Estimation of representative value of road-traffic noise level and air pollutants

The representative value of road-traffic noise level of a grid cell was calculated based on existing façade noise map. The noise map of Gwangju was created by commercial noise mapping software, SoundPLAN 7.4.(6) The power averaged façade noise level of each grid cell was calculated and defined as representative road-traffic noise level of a grid cell. And the representative value of air pollutants of grid cell was calculated base on existing air pollutants map. The air pollutants map was created by two software. The emission level was calculated by MOVES(Motor Vehicle Emission Simulator) developed by US EPA(Environmental Protection Agency).(7) And the R-line 1.2 which calculate air pollutants dispersion in atmosphere was used to calculate representation value of air pollutants concentration.(8) Carbon monoxide(CO) and PM2.5 concentrations were used as representative value of air pollutants. Figure 2 shows the noise map of Gwangju. And figure 3 shows the air pollutants map of Fulton.

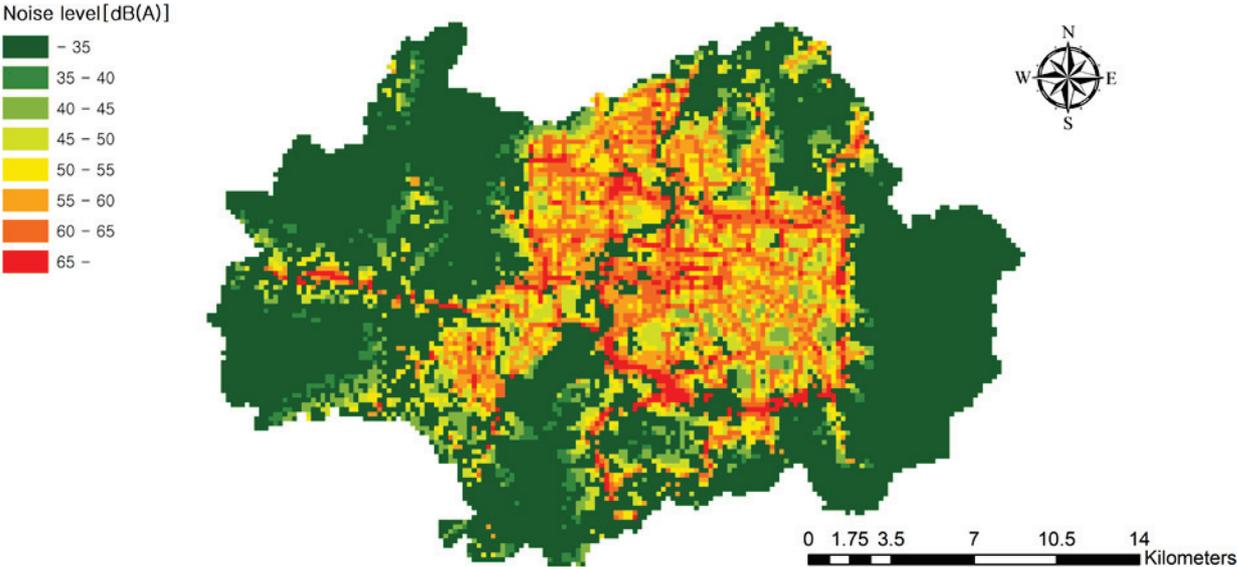


Figure 2 – Road-traffic noise map of Gwangju

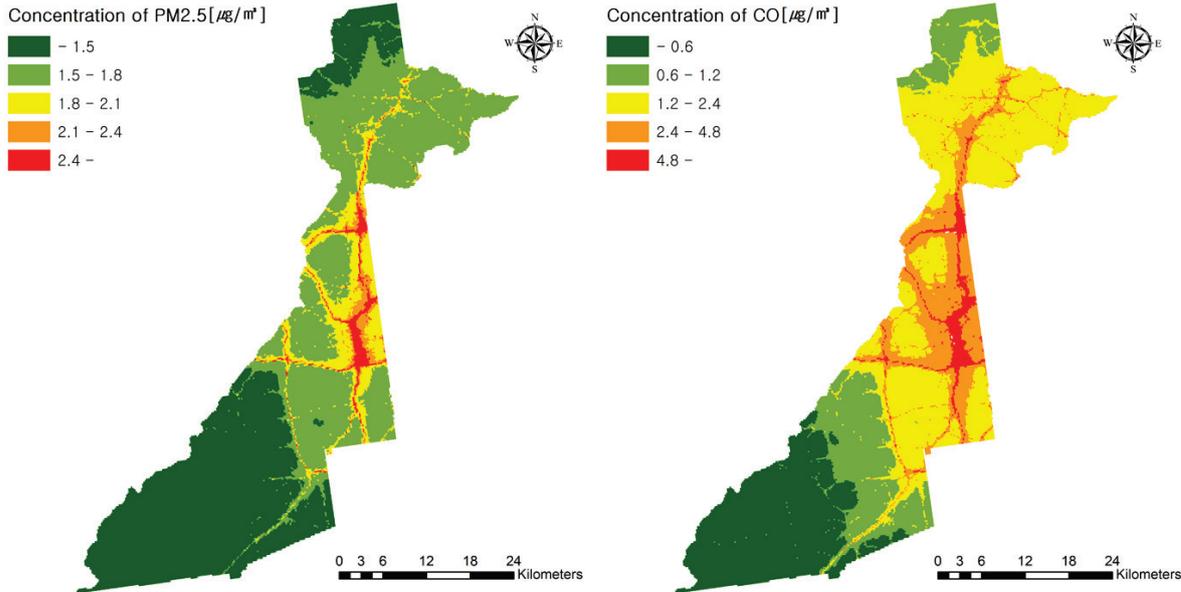


Figure 3 – Air pollutants map of Fulton

2.3 Estimation of representative value of urban form indicators

The 3D urban models of each city used to extract representative value of urban form indicators. The models were created using ArcMap 10.3.(9). The urban form indicators fall into four categories, population, building road and land-use-related.(10) Population density(Pd) was chosen as population-related urban form indicator. The data of Gwangju includes the population data, but the data of Fulton did not include population data. So, in this study, the population-related urban form indicator was excepted. Similarly as in our previous study, Ground Space Index(GSI) and Floor Space Index(FSI) were chosen as building-related urban form indicators.(4, 10) Traffic volume(Q), heavy-vehicle ratio(PH), traffic speed(V) and road area density(Ra) were chosen as road-related urban form indicators.(4, 10) Land-use-related urban form indicators are consist of residential(LR), commercial(LC), industrial(LI) and green(LG) area ratios.(4, 10) The calculation formula and definition of urban form indicators were shown in Table 1.

Table 1 – Formula and definition of urban form indicators

| Type | Variable | Calculation formula | Definition of variables in formula |
|------------------|---|------------------------------------|--|
| Building-related | Ground space index (GSI, m ² /m ²) | $GSI = \frac{\sum_k G_k}{A}$ | G_k : building coverage of building k A : area of each grid cell(40,000m ²) |
| | Floor space index (FSI, m ² /m ²) | $FSI = \frac{\sum_k G_k F_k}{A}$ | G_k : building coverage of building k F_k : number of floors of building k A : area of each grid cell(40,000m ²) |
| Road-related | Traffic volume (Q, vehicles/h) | $Q = \frac{\sum_i Q_i R_i}{R_i}$ | Q_i : traffic volume of road i R_i : length of road i |
| | Heavy vehicle ratio (PH, %) | $PH = \frac{\sum_i PH_i R_i}{R_i}$ | PH_i : heavy vehicle ratio of road i R_i : length of road i |
| | Traffic speed (V, km/h) | $V = \frac{\sum_i V_i R_i}{R_i}$ | V_i : traffic speed of road i R_i : length of road i |
| | Road area ratio (Ra, m ² /m ²) | $Ra = \frac{\sum_i R_i w_i}{A}$ | R_i : length of road i w_i : width of road i A : area of each grid cell(40,000m ²) |
| Land-use-related | Residential area ratio (LR) | $LR = \frac{L_{Ra}}{A}$ | L_{Ra} : area of residential area A : area of each grid cell(40,000m ²) |
| | Commercial area ratio (LC) | $LC = \frac{L_{Ca}}{A}$ | L_{Ca} : area of commercial area A : area of each grid cell(40,000m ²) |
| | Industrial area ratio (LI) | $LI = \frac{L_{Ia}}{A}$ | L_{Ia} : area of industrial area A : area of each grid cell(40,000m ²) |
| | Green area ratio(LG) | $LG = \frac{L_{Ga}}{A}$ | L_{Ga} : area of green area A : area of each grid cell(40,000m ²) |

3. ARTIFICIAL NEURAL NETWORK ANALYSIS

3.1 Model development

Artificial neural network method was used to analyze the relationship between urban form indicators and road-traffic noise, air pollutants. The whole dataset of Gwangju which is consist of urban form indicators and road-traffic noise level, were divided two, training dataset and test dataset. The artificial neural network model for analyzing relationship between urban form indicators and road-traffic noise were fitted by training dataset. And explanatory power of the model was verified by test dataset. The number of training and test dataset is 3,955 and 1,978. In the process of fitting artificial neural network model, training dataset was divided into training and verification dataset. Difference between road-traffic noise level predicted by artificial neural network model and that of noise map was calculated by mean squared prediction error(MSE). Similarly, to analyze the relationship between urban form indicators and air pollutants, the whole dataset of Fulton county was divided into training and test dataset. The number of training and test dataset is 17,811 and 8,906. Error analysis was also performed as in the case of noise.

Artificial neural network model is based on mathematical calculations finding the point where the error between existing data and predicted data is minimized. Because it is through complicated calculation process, statistical analysis software R, which could be performed automatically, was used.(11) R has various package to create artificial neural network model. The nnet package which could create artificial neural network model including single hidden layer was used.(12)

The optimized artificial neural network model could be fitting by change of various parameters. In this study, the number of hidden nodes, decay parameter which prevent over-fitting to test dataset were changed. Maxit parameter which specifies the maximum number of repetitions in fitting process was fixed to 200, and the other parameters were applied as default. The number of hidden nodes was changed 1 to 50, decay parameter was changed e^{-2} to e^7 and 0.

In case of road-traffic noise, the artificial neural network model was optimized when the number of hidden nodes was 48 and decay parameter was e^{-2} . And in case of CO, the number of hidden nodes was 38, decay parameter was e^{-2} , and in case of PM2.5 the number of hidden nodes was 13, decay parameter was 0. The example of finding minimum MSE were shown in Figure 4.

4. Result

4.1 Model application to test dataset

The three artificial neural network models(road-traffic noise, CO, PM2.5) were applied to test dataset to analyze explanatory power. The correlation coefficient of road-traffic noise level based on noise map and that of artificial neural network model was 0.74. In case of CO, the correlation coefficient was 0.74 and in case of PM2.5 correlation coefficient was 0.75. The detailed correlation coefficient and coefficient of determination were shown in Table 2.

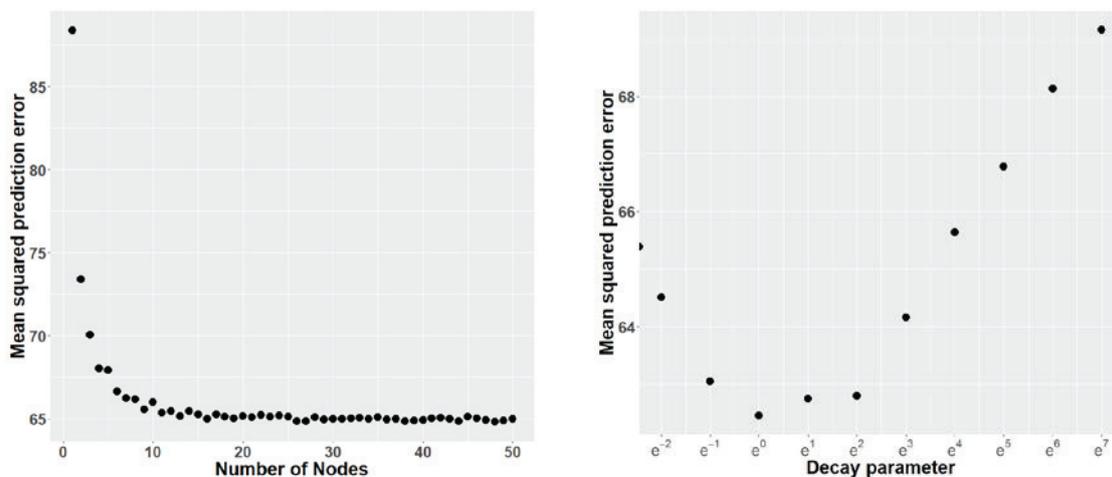


Figure 4 - Mean squared prediction error of road-traffic noise by changing number of hidden nodes and decay parameter

Table 2 –Correlation coefficient and coefficient of determination

| | Correlation coefficient(r) | R-squared (R ²) | Adjusted R-squared(R ² _{adj}) |
|---------------------|----------------------------|-----------------------------|--|
| Noise level | 0.74 | 0.54 | 0.54 |
| CO concentration | 0.74 | 0.54 | 0.54 |
| PM2.5 concentration | 0.75 | 0.56 | 0.56 |

Figure 5 shows the comparison between predicted road-traffic noise level based on noise map and road-traffic noise level based on artificial neural network model.

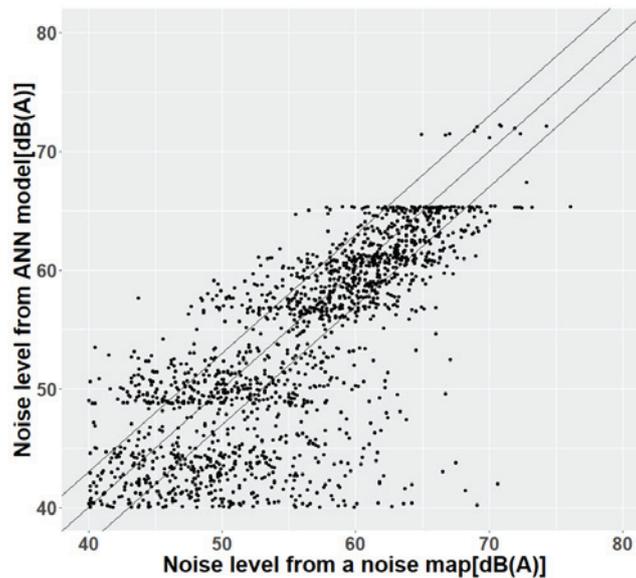


Figure 5 – Comparison between noise levels from a noise map and ANN model

Figure 6 and 7 show the comparison between predicted CO and PM2.5 concentration based on noise map and CO and PM2.5 concentration based on artificial neural network model.

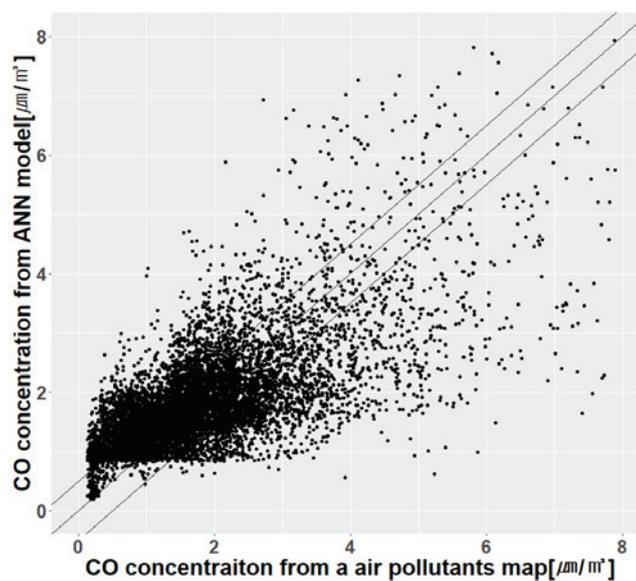


Figure 6 - Comparison between CO concentrations from a noise map and ANN model

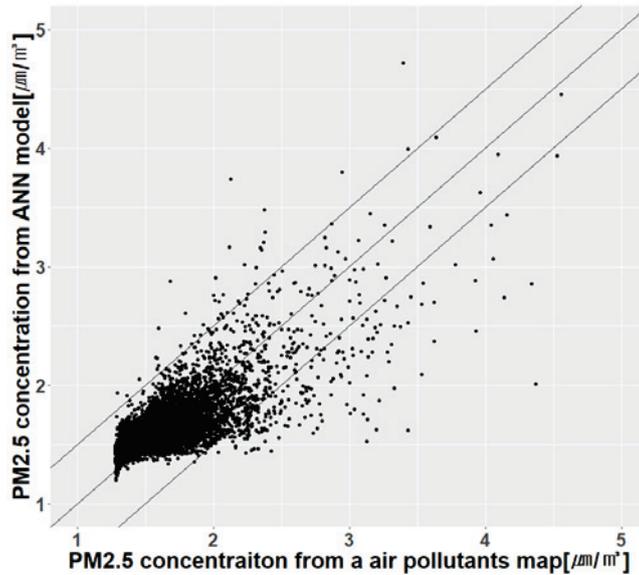


Figure 7 - Comparison between PM2.5 concentrations from a noise map and ANN model

4.2 Relative importance of urban form indicators

The Garson algorithm was used to analyze the relative importance of urban form indicators on the generation of road-traffic noise and air pollutants. The NeuralNettools package which includes Garson analysis was used.(13) In case of road-traffic noise, relative importance of urban form indicators was in order of FSI, GSI and LI. In case of CO, relative importance of urban form indicators was in order of FSI, V and LR. And in case of CO, relative importance of urban form indicators was in order of LC, Ra and FSI. Figure 8 shows the relative importance of urban form indicators when predict road-traffic noise level and concentration of CO and PM2.5 based on artificial neural network model.

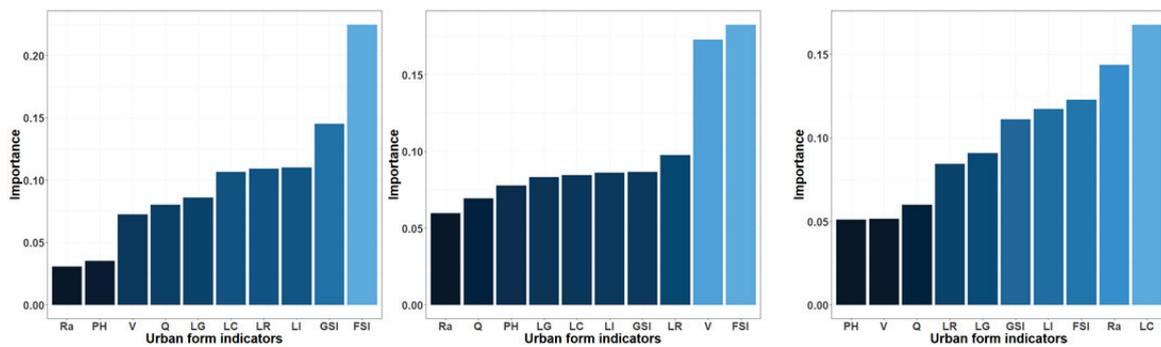


Figure 8 – Relative importance of urban form indicators in road-traffic noise, CO and PM2.5 prediction

5. SUMMARY

The artificial neural network model was fitted to analyze relationship between urban form indicators and road-traffic noise, air pollutants. Artificial neural network model which is prediction road-traffic noise level’s explanatory power was 0.54. In case of CO concentration explanatory power was 0.54 and in case of PM2.5 concentration explanatory power was 0.56. Road-traffic noise level, CO and PM2.5 concentrations which were predicted by artificial neural network model shows linear relationship with predicted result of nose and air pollutants map. As a result of analyzing relative importance of urban form indicators on the generation of road-traffic noise and air pollutants, the importance of urban form indicators was different by pollutant’s type. The most significant urban form indicator was FSI

ACKNOWLEDGEMENTS

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2017R1D1A1B03035253)

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