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Crossroad Traffic Load Estimation Based on the Noise Level Measurement

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ABSTRACT
The article presents a method of a crossroad traffic load estimation based on the registered noise level. Data on the current noise level and the equivalent traffic intensity for the selected crossroad was recorded as part of the test installation of the road traffic impact assessment system for the acoustic climate. The measurement was carried out continuously over a few-month period. Based on the collected data, the analysis of variability of registered noise levels was carried out in relation to changes of equivalent traffic load and selected environmental parameters: temperature and relative air humidity. The use of artificial neural network has been proposed for estimating traffic load. On the basis of the equivalent noise level for the fifteen-minute interval and the values of environmental parameters averaged over the same period of time, the equivalent traffic load within the crossroad shall be determined.

KEYWORDS: traffic, crossroad, noise, estimation

1. Introduction

Noise, alongside exhaust emission, is considered to be one of the most important environmental pollutants in urban areas. The main sources of noise emission in a vehicle are the exhaust and drive systems, and tire-pavement friction, however, the noise level generated by road transport is affected by many other factors, such as: number and class of vehicles, infrastructure, traffic conditions, local buildings, meteorological conditions.

Excessive traffic congestion is becoming an increasingly important issue in urban areas, often determining the quality of the acoustic climate. According to EUROSTAT (Statistical office of the EU), between 1996 and 2015, Poland recorded the highest average annual growth rate of vehicles per capita within the EU countries (EU28), at the level of 5.21% [Stock of vehicles at regional level. Eurostat]. According to estimates of the European Automobile Manufacturers' Association ACEA, in 2015 Poland was ranked 4th in the EU in terms of motorization rate (628 vehicles/1000 inhabitants), thus exceeding the EU average (573 vehicles/1000 inhabitants) [2].

However, the necessity of transport tasks in the presence of a growing passengers flow and freight is in conflict with public health. Excessive noise severely damages human health and disrupts everyday life. The effects of exposure to noise include sleep disorders, cardiovascular and psychophysiological diseases, reduced work efficiency, fatigue, irritation and changes in social behavior.

According to European Union it is estimated that [3]:

- around 40% of the EU's population is exposed to traffic noise levels of more than 55 dB (A);
- 20 % is exposed to levels exceeding 65 dB (A) during the day;
- more than 30% is exposed to levels exceeding 55 dB (A) at night.

Since it is not possible to completely eliminate road traffic and its effects from city centers, it seems crucial to implement monitoring of the road transport environmental impact. This need was recognized by the bodies of the European Union by issuing Directive 2002/49/EC of the European Parliament and the Council of 25 June 2002 relating to the assessment and management of environmental noise. One of its main assumptions is to determine the level of exposure to environmental noise by assessment methods common to the

Member States through preparation of noise maps updated every five years [4].

The existing relationship between recorded sound levels and traffic parameters is most often used to calculate the noise pollution level [5]. In the paper authors propose the reverse approach - a method of estimating the traffic load of the crossroad based on registered noise level.

2. A research object

Currently, in order to reduce the level of air pollution and noise level and to pursue the provisions of the Directive, advanced environmental monitoring systems are implemented to support the activation of short-term actions and management strategies. The data enabling the implementation of the model to estimate the crossroad traffic load was recorded using the prototype installation of air quality and the acoustic climate monitoring system. The system is an extended version of an OnDynamic [6]. The base station of the system, in accordance with the functionality assumed at the designing stage, records and provides access to traffic data and the values of individual indicators characterizing the environmental impact of transport in near real time. Currently, prototype base stations of the system have been installed at several locations of the road network of the city of Bielsko-Biala (Fig. 1). Data on the current noise level and equivalent traffic volume of vehicles analyzed in the further part of the study were recorded in the period from late July to early November at the station located at the crossroad of Pilsudskiego and Komorowicka Streets (Fig. 2). This location is characterized by the most unfavorable local building configuration in comparison with other locations [7].

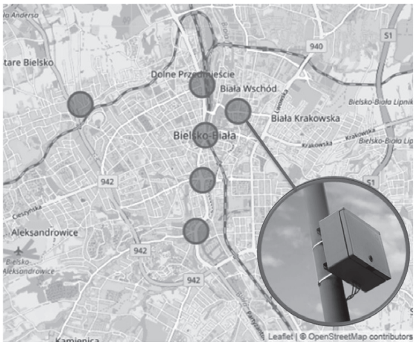

Fig. 1. Location of the base test stations for air quality and acoustic climate measurement system in Bielsko-Biala [own study]

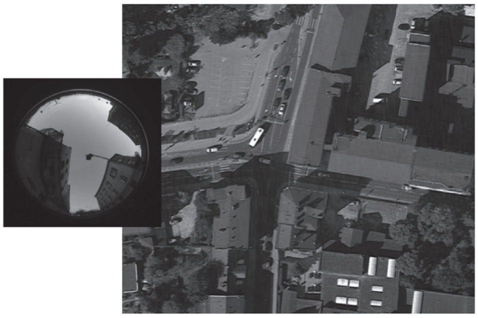

Fig. 2. The crossroad of Pilsudskiego and Komorowicka Streets with unfavorable local building configuration [own study]

The equivalent noise equivalent data were averaged over the period T=15 minutes, according to the formula:

$$L_{Aeq0T} = 10\log\left[\frac{1}{T}\sum_{k=1}^{n} t_k 10^{0,1L_{Akiqtk}}\right] \quad \textbf{(1)}$$

where:

T – reference time interval [s],

t_k – the period of recording results [s],

$L_{Aeq\,tk}$ – an equivalent sound level A at the period of recording results t_k, in decibels [dB],

n – number of periods of recording results t_k.

The noise levels at base stations are measured using SparkFun's low-cost sound detection systems which, however, ensure sufficient measurement accuracy [8].

Using the data collected by the base station, an analysis of variability of recorded noise levels with regard to changes in the equivalent traffic load was carried out (Fig. 3).

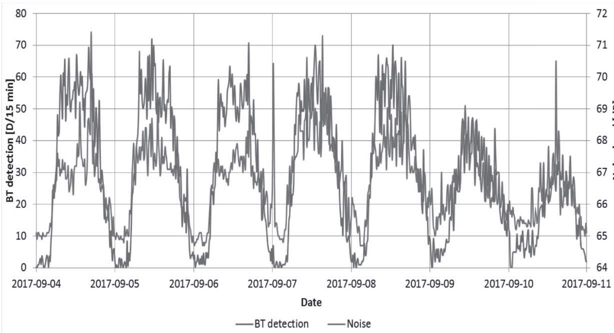

Fig. 3. Equivalent traffic and noise level for the sample data recording week [own study]

The data set on the noise intensity recorded during the analyzed time period for the selected crossroads is characterised by the fact that identical values of equivalent noise intensity were recorded for different traffic load conditions of the crossroads. Thus, it means that the isolated noise level measurement does not allow to identify the degree of crossroad traffic load (Fig. 4).

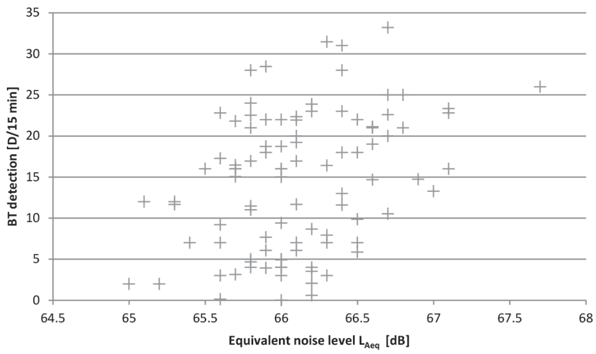

Fig. 4. The ratio of the noise intensity to the different traffic load conditions for the selected measurement day [own study]

3. Application of an artificial neural network to predict the crossroad traffic load level

The elimination of ambiguity requires the introduction of additional parameters, representing the local state of the ambient (atmosphere), that have an impact on the measured noise levels [9, 10]. Therefore simultaneously with the measurement of traffic load and noise level intensity, a continuous measurement of temperature and relative air humidity was carried out. Unfortunately simple correlation between the noise level and environmental parameters does not exist (Fig. 5, Fig. 6). However data on environmental conditions will also be included in further analyses.

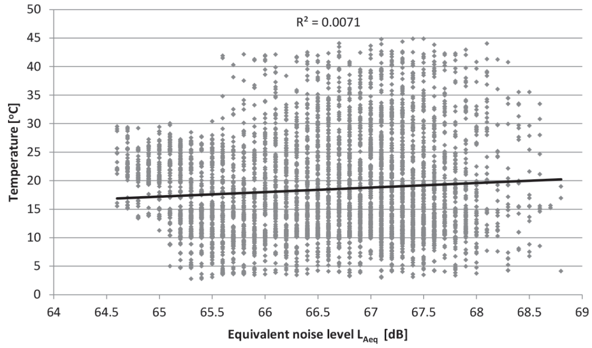

Fig. 5. Correlation between the noise level and the air temperature [own study]

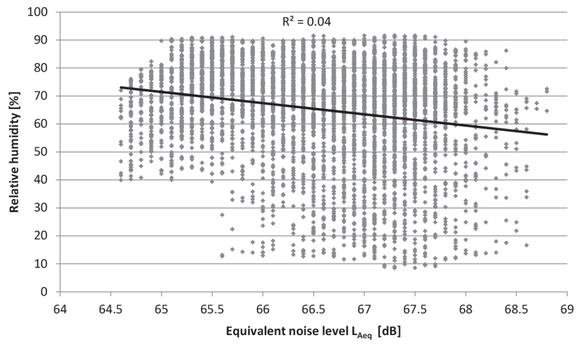

Fig. 6. Correlation between the noise level and the relative air humidity [own study]

A set of measurement data in relation to the recorded values of environmental parameters: temperature and relative air humidity and the equivalent noise level is shown in Fig. 7. A model that takes into account all three mentioned parameters is proposed in the further part of the chapter.

Due to the way of collecting data on crossroads traffic load using OnDynamic Bluetooth detectors, in the next step it is suggested that the problem of estimating the traffic load of crossroads should be reduced to indicate the discrete range of variation of traffic load, instead of estimating the percentage of this load. This is because the Bluetooth detection system allows only to detect objects with active communication devices. Tests carried out in the city of Bielsko-Biala showed that this method of detection enables to detect about 20-30% of vehicles [11]. In addition, attention should be paid to potential disturbances in the level of estimation associated with the detection of pedestrians and other objects that do not represent vehicles. This is partly compensated by the data filtration mechanisms and algorithms used within the OnDynamic system. Additionally, as part of the conducted work, in order to eliminate artefacts associated with the detection of BT devices, the average detection levels for particular hours and the type day of the week (Fig. 8). This approach allowed to determine limit values for the percentage ranges of variation.

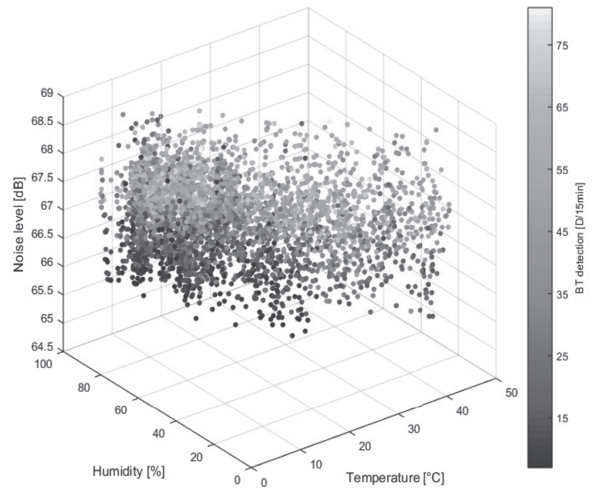

Fig. 7. The relation between measurement data and recorded environmental parameter values [own study]

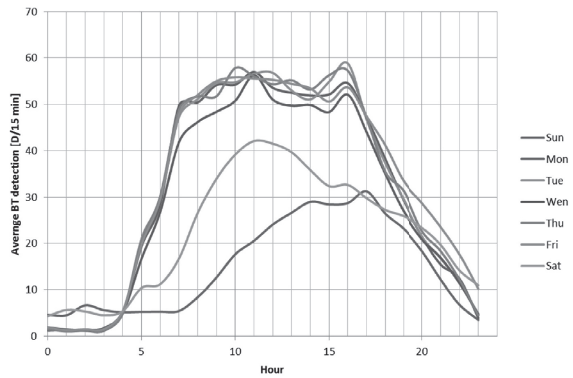

Fig. 8. Average detection levels for each hour of data logging by day type [own study]

As a result, the analyzed set of data will consist of five discrete traffic load classes; each of the ranges will cover a 20% of the maximum traffic load. Fig. 9 shows a histogram presenting the size of the data set in relation to the adopted traffic load classes.

In order to estimate the traffic load level (TLL) an artificial neural network model with three inputs signal and one output signal was proposed. It was considered that it will be feed-forward multi-layer neural network i.e. with one or more hidden layers (Fig. 10.).

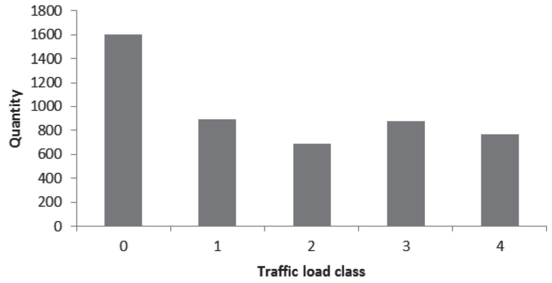

Fig. 9. The number of the data set in relation to the adopted traffic load classes [own study]

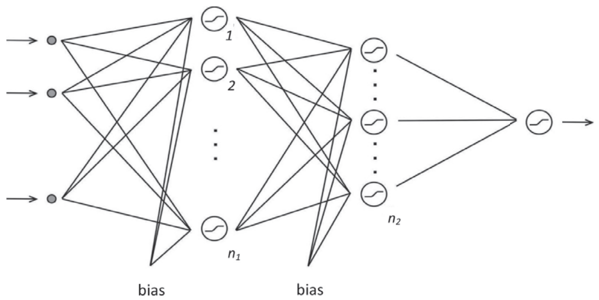

Fig. 10. Basic schematic of the architecture of the feed-forward multi-layer neural network [own study]

In the proposed model, the network output signal is calculated as the nonlinear transformation of input signals, upon the assumption that the activation function for each of the network neurons is a bipolar function of the following form:

$$f\left(w^t z\right) = 2\left[1 + e^{-\lambda w^t z}\right]^{-1} - 1 \quad \textbf{(2)}$$

where:
w – vector of weight used for neuron input signals,
z – vector of neuron input signal,
λ – coefficient defining the range of linearity.

The value of the activation function for each of the neurons constituting the first hidden layer of the network depends directly on the input signals to the network, taking into account the varying weights. In the model considered in the study, the input signals are:

- the values of the recorded equivalent noise level for a 15-minute time period,
- information on average air temperature,
- information about the average relative air humidity.

In case of the last two quantities, it was decided to use discrete representations in the form of twenty classes, comprising determined both parameters variability ranges. The range of variability of the individual parameters constituting the input signals is shown in Table 1. It is worth to noting that both the temperature and humidity of the air are recorded for samples of air injected into the measuring system inside the base station.

Table 1. Characteristic of the input signals [own study]

Parameter	Min	Max	Average	Median	Range covered by a single class
Equivalent noise level [dB]	64.6	68.8	66.5	66.6	not applicable
Air	2.7	44.8	18.4	16.7	5
Relative humidity [%]	8	92	65	69	5

In the proposed model the network have neural connections of the each-to-each type. The input layer signals are subsequently processed by each of the neurons of the first hidden layer according to the adopted activation function [12], and the resultant signal will be transferred to each of the neurons of the next network layer. Expected information about the traffic load factor is calculated on the last layer with single neuron. Taking into account a last hidden layer with k elements, the value of the estimated traffic load level is calculated as:

$$TLL = f\left(\sum_{i=1}^{k} w_i \cdot z_i\right) \quad \textbf{(3)}$$

The functionality of the proposed model depends on the correct identification of its parameters, i.e. unknown weight vectors. The process of weight vector identification is called the neural network learning. Network learning, which consists in modifying the weights of individual connections between the neurons forming the network, is executed until the properly formulated stop criterion making the quality measure of the traffic load factor estimation will be achieved.

For the network learning the momentum method was used with incremental updating of weights, i.e. in step n+1 of network learning the weights were modified according to the formula [12]:

$$w^{(n+1)} = w^{(n)} - \eta^{(n)} \nabla\Omega\left(w^{(n)}\right) + \delta\left(w^{(n)} - w^{(n-1)}\right) \quad \textbf{(4)}$$

where:
η – learning coefficient,
Ω – goal function in the form of mean square error of network's response relative to the values expected for a given input signals,
δ – moment coefficient.

Simultaneously in each step learning coefficient has been modified according to formula [12]:

$$\eta^{(n+1)} = \begin{cases} 0.7\eta^{(n)} for \Omega^{(n)}\left(\Omega^{(n-1)}\right)^{-1} > 1.06 \\ 1.15\eta^{(n)} otherwise \end{cases} \quad \textbf{(5)}$$

In this paper, it is assumed that once the network architecture is established, it will be trained until the network reaches an estimation efficiency at the level of ⅔ cases for data from the training set.

The assumption of such a condition was given by the significant noise contained in the set of measurement data. It mainly covers the highest and lowest traffic load classes, which accounts for almost 50% of all cases. Noise means that in the case of many traffic load measurement results, there is no significant correlation with the recorded noise level. This is a consequence of the limitations of traffic load registration using the OnDynamic system in conditions of low traffic and high congestion. For establishing a training set a subset of data randomly separated from the measurement dataset was used. The training set is covering a total of 30% of all.

A diagram of the procedure for determining network architecture, teaching and verification criterion is shown in Fig. 11.

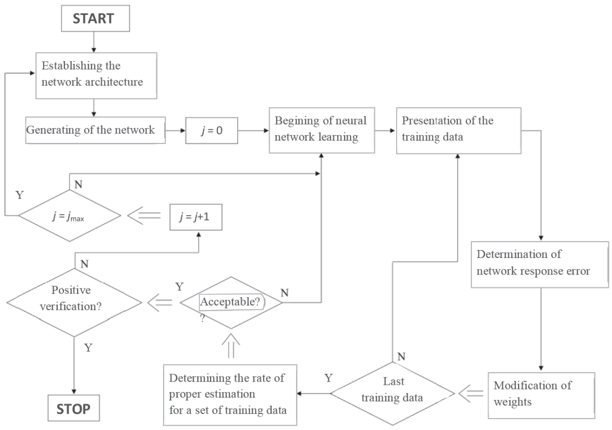

Fig. 11. Diagram of the procedure used to determine the architecture and training the network [own study]

It can be noticed that in the learning process a random choice of weights was used after every iteration of network training and random determination of training patterns. If for a given network architecture after applying many iterations the assumed value of the stop condition was not reached, the architecture was modified (once the specified number of repetitions -j_{max} is reached).

Finally, applying the procedure described above, the network architecture of 3-6-3-1 was established. It means that there are 6 neurons on the first hidden layer, and 3 neurons on the second hidden layer. The network learning process proceeded relatively quickly, the expected accuracy for the training set was obtained after just over three hundred learning cycles. Changes in the η-value during network training with a target architecture of 3-6-3-1 is shown in Fig. 12.

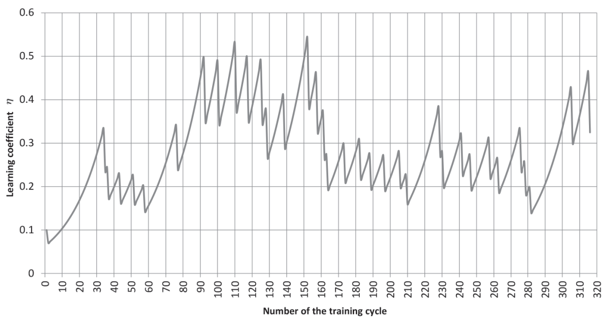

Fig. 12. Change in the learning coefficient η in individual training cycles [own study]

The neural network with the weights established during the learning process was then used to estimate the level of traffic load for three times larger data sets than the training set. On such basis, it was concluded that the proposed model, using information on the equivalent noise level and discrete ranges of temperature and relative humidity, allows estimating the traffic load level of the analyzed crossroads with an efficiency of 60%. The set of the data which was properly estimated using the model is presented in Fig. 13.

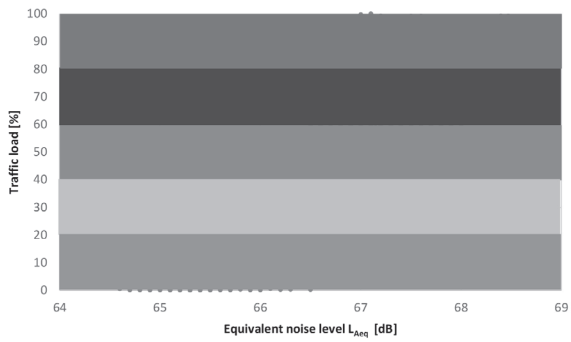

Fig. 13. The set of the data estimated using the model [own study]

However, the estimation efficiency for each traffic load class varies from slightly over 55% to 63%. At the same time, this is an appropriate estimation efficiency for the highest and lowest traffic load class respectively. The estimation efficiency for each of the considered discrete traffic load classes is shown in Fig. 14.

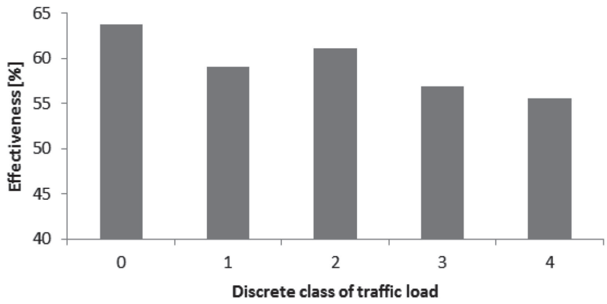

Fig. 14. A summary of the estimation effectiveness in relation to individual traffic load classes [own study]

The estimation effectiveness analysis for the remaining traffic load classes indicates a maximum of 5% efficiency discrepancy for classes 1-3. Results indicate in principle a significant level of homogeneity of estimation efficiency in the context of the considered discrete traffic load classes.

4. Conclusion

The stations of the traffic impact assessment system on ambient air quality and the acoustic climate from which the data were obtained are located in the areas of crossroads. Recorded noise level depends on a number of variables, such as traffic volume, class of vehicles, directional structure, traffic management and also intersection geometry. The literature also shows a connection with traffic conditions and the level of service [13,14]. Therefore, the use of the proposed estimation method for a crossroads other than those considered in the study requires a re-learning process of the network. On the other hand, increasing the accuracy of traffic load estimation would require the following actions at the data collection and network learning stage:

- increase the precision and accuracy of total traffic flow measurement at the crossroads,
- recording information on the occurrence or absence of precipitation,
- wind speed recording.

According to the authors, a less noisy input set and extension of the model through the introduction of two additional input signals will allow to increase the efficiency of traffic load estimation.

In conclusion, it was found that the use of an environmental monitoring station enables estimation of the traffic load of crossroads, which may be an interesting added functionality in the case of monitoring of crossroads without traffic detection system.

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