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Comparison between multiple linear regressions and artificial neural networks to predict urban sound quality

Laurent Brocolini (1), Lory Waks (2, 3), Catherine Lavandier (1), Catherine Marquis-Favre (2), Mathias Quoy (4), Mathieu Lavandier (2)

(1) Université de Cergy Pontoise, LMRTE, F-95000 Cergy-Pontoise, France
(2) Département Génie Civil et Bâtiment, Rue Maurice Audin, F-69518 Vaulx-en-Velin cedex, France
(3) Ministère de l'Ecologie, de l'Energie, du Développement Durable et de la Mer, Mission Bruit et Agents Physique, La Grande Arche Paroi Nord, F-92055 La Défense cedex, France
(4) Université de Cergy-Pontoise, ETIS, UMR 8051, F-95000 Cergy-Pontoise, France

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ABSTRACT

The purpose of this study was to develop a predictive model of urban sound quality from field survey data using multiple linear regressions and artificial neural networks (ANNs). In order to determine a soundscape pleasantness model, passers-by were asked to assess their environment mainly from an acoustic point of view but also from a global perspective (visual and air quality). Users were asked to evaluate the sound environment firstly as a whole and secondly listening to each perceived sound source. The investigation took place at the "Parc de la Tête d'Or" which is an urban park in the French city of Lyon, in two locations on both sides of the main park access. One hundred and twenty subjects, divided equally between the two locations and the three periods of the day (morning, afternoon and evening), were interviewed. Each one had to evaluate twenty-six subjective variables on a rating scale from 0 to 10. In order to propose a relationship between the soundscape pleasantness and the others twenty-five assessed variables, the collected data have been analysed according two models: multiple linear regressions and predictive method based on artificial neural networks were used and compared. The first method is useful to understand which variables explain the assessment of the soundscape pleasantness, but not the second one which can be considered as a "black box". However ANNs seem to better predict the soundscape pleasantness when a new set of data is tested.

INTRODUCTION

Today, citizens, authorities, researchers, everybody is concerned about urban quality (visual, sound, air pollution …).

The aim of the PREDIT research project, QUASOART is to define an urban soundscape quality indicator which has to be easily displayed on maps and readable by everybody. Supported by the French Energy Agency ADEME, this project brings together different partners: "MRTE" and "ETIS" laboratories of the University of Cergy-Pontoise, "ENTPE" and "Bruitparif". Part of this research, the study presented here aims at developing a predictive model of urban soundscape quality using two distinct approaches which are to be compared i) one based on neural networks learning methods, and ii) a second using statistical techniques, namely multiple linear regressions. The reasoning used is as follows. Through a questionnaire the soundscape pleasantness felt by passers-by, as well as a number of other subjective variables, are collected. From this data it is possible to find a relationship between soundscape pleasantness and the various explanatory variables.

In addition to this relationship, and by relying on cross-validation method [1], we have paid attention to the capacity of the established models to predict a sound pleasantness value when new data are provided.

METHODOLOGY

Locations and periods of the study

Field survey was conducted at the "Parc de la Tête d'Or". Very popular, this is a large urban park located in the city of Lyon, in France, bordered by two large boulevards. To collect the passers-by assessments the investigation took place in two locations on both sides of the main entrance. Both locations are about ten meters from the entrance, one inside the park (location L1) and the other outside (location L2). At these locations there are not homogeneous sound environments but instead what we might call "transition area" [2]. Actually, many sound sources are present. Completed in the month of March and April 2009, we have voluntarily excluded for this study Saturdays and Sundays as well as the Monday mornings, Wednesdays and Friday afternoons that could be different from the classical soundscape working day. Furthermore, the day was divided into three periods: 9 am - 11 am, 2pm – 4pm and 5 pm - 7 pm. On the one hand these time slot match up with the hours attending park and on the other hand they might offer a certain variability of soundscape during the day [3].

Questionnaire

The aim of the survey was to gather people's perception of their environment at the place and during the time of the interview (about ten minutes). Based on previous studies [4, 5, 6, 7], it mainly consists of closed questions in the form of semantic differential with a continuous graduated scale. Subjects had to respond with a cross on the scale, see Figure 1.

Figure 1. global pleasantness scale

The survey was made so that respondents first consider the environment from a global perspective, and then dwell on various aspects of the environment (acoustic, visual, air quality) but still in their entirety and finally end with the identification of the sound sources. Thus the questionnaire can be divided into five parts.

For the first part of the questionnaire, subjects were asked to assess the overall environmental quality, telling in a few words why they thought it was pleasant or unpleasant and note this pleasantness on the presented scale (Figure 1).

Subsequently people were asked to focus on the sound environment as a whole, and then answer questions about different characteristics. For a better understanding an explanation was given under each adjective, see Figure 2.

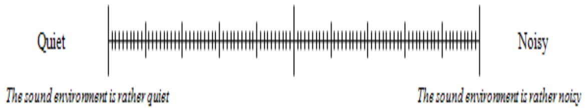

Figure 2. example of question on the sound environment

In the third part subjects were asked to assess the visual pleasantness, the perception of the air quality but also to evaluate the familiarity of the soundscape.

The fourth part of the questionnaire concerned the sound sources. Subjects were asked to focus on sound sources, to specify which ones they were able to identify and for each one to estimate their loudness and their time ratio of presence (based on the duration of the survey). After that, a sound sources list was given and subjects could clarify if they noticed or not these sound sources and if so rate their loudness and time ratio of presence see Figure 3.

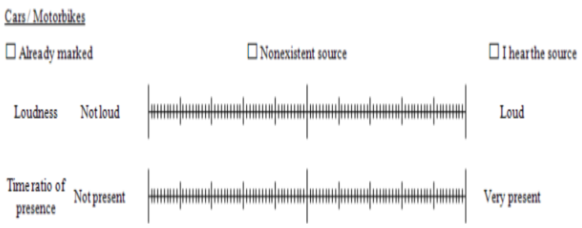

Figure 3. example of sound sources marking

Finally, subjects were asked if they thought the sound environment was suitable for their activity.

Table 1 presents all the variables measured for each subjects. Each variable was noted on the same scale and was linearly transformed into a value ranging from 0 to 10.

Table 1. Measured variables

	Measured variables	
Pleasantness	(1) Sound pleasantness	
	(2) Global pleasantness	
	(3) Visual pleasantness	
	(4) Perceived air quality	
Soundscape characteristics	(5) Quiet / Noisy	
	(6) Stable / Changing	
	(7) Lifeless / Lively	
	(8) Enveloping / Not Enveloping	
	(9) Surprising / Familiar	
	(10) Unsuitable / Suitable	
Sound Sources	(11) PL_LV	Cars / Motorbikes
	(12) TP_LV	(Light Vehicles)
	(13) PL_Mop	Mopeds
PL	(14) TP_Mop	
=	(15) PL_TB	Trucks/Buses
Perceived	(16) TP_TB	
Loudness	(17) PL_H	Horns
	(18) TP_H	
	(19) PL_Act	Activities
	(20) TP_Act	
TP	(21) PL_HP	Human Presence
=	(22) TP_HP	
Time ratio	(23) PL_Bir	Birds
of presence	(24) TP_Bir	
	(25) PL_Nat	Nature
	(26) TP_Nat	

Subjects

One hundred and twenty passers-by were interviewed, sixty at each location, twenty per period. The only personal data collected on subjects are gender and age category, which was evaluated by the expert following three classes: youth, adult, elderly person. However these personal factors were not used in the analysis. For information, about 54% of respondents were women for 46% of men, most of them adults.

Variables selection

Once the data are collected (60 subjects x 26 variables) it is very useful to select relevant variables for the construction of the predictive models (multiple linear regressions and artificial neural networks). We wanted to explain sound pleasantness (dependent variable) from the other subjective variables (independent variables). However, among all these variables, some might give similar information and it is therefore interesting to keep only the most relevant ones. Furthermore, given the limited number of subjects, reducing the number of variables may be beneficial to develop the models.

Based on the Bravais-Pearson correlation coefficients between each pair of independent variables to the 95 % confidence interval we rejected the following variables with the aim of proposing soundscape pleasantness models:

- the global pleasantness, correlated with the noisiness and the visual pleasantness,

- the perceived air quality, correlated with the visual pleasantness, the familiarity and the suitability of the soundscape to the present activity,

- the liveliness, correlated with the noisiness and the familiarity.

Moreover, the correlation coefficients showed that among all the sound sources, the loudness was always highly correlated with the estimated time ratio of presence. Based on a previous study on the contribution of the sources in the characterization of sound environments [8], the time ratio of presence seemed to be a better indicator than loudness to explain the perceived sound environmental quality. So this indicator was kept.

We also paid attention to the responses repartition. Indeed, variables histograms show some variability in the answers. It appeared that sources related to road traffic in location L1 inside the park, except light vehicles, had a zero mode, see Figure 4. In the location L2, outside, only the mopeds had no variability.

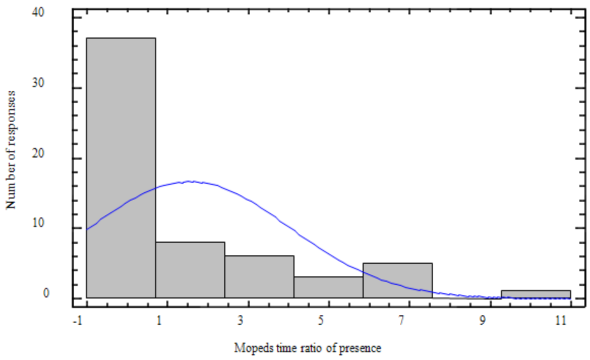

Figure 4. histogram of the mopeds time ratio of presence (L2)

Although they were clearly identifiable by the expert during the interview, subjects generally told not to hear these sources. In the same way subjects have not heard the sound sources "activities" and "nature's elements".

Table 2. Variables chosen to explain the sound pleasantness in location 1 (L1)

	Nomenclature	Measured variables
Dependent variable	S_PL	Sound pleasantness
Independent variables	V_PL	Visual pleasantness
	Nois	Noisiness
	Dyn	Dynamic
	Env	Envelopment
	Fam	Familiarity
	Suit	Suitability
	TP_LV	Light Vehicles
	TP_HP	Human Presence
	TP_Bir	Birds

In summary, to explain the sound pleasantness we have chosen nine independent variables for location L1 inside the park (see Table 2) and eleven independent variables for the location L2 (see Table 3).

Table 3. Variables chosen to explain sound pleasantness in location 2 (L2)

	Nomenclature	Measured variables
Dependent variable	S_PL	Sound pleasantness
Independent variables	V_PL	Visual pleasantness
	Nois	Noisiness
	Dyn	Dynamic
	Env	Envelopment
	Fam	Familiarity
	Suit	Suitability
	TP_LV	Light Vehicles
	TP_TB	Trucks / Buses
	TP_H	Horns
	TP_HP	Human Presence
	TP_Bir	Birds

ANALYSIS

Multiple linear regressions

The multiple linear regression analysis is a method that allows studying the relationship between a dependent variable (in our case the sound pleasantness) and independent variables [9]. An adjusted model with fewer variables might have been chosen here, but the purpose of our study was to compare multiple linear regressions with neural networks. For this reason, we kept the model involving all selected variables (nine for location 1 and eleven for location 2).

Artificial neural networks

Result from several disciplines (physics, psychology, biology ...), the artificial neural networks are a computation method which is inspired by the structure of biological neurons. Today they are very useful in many fields (aerospace, automobile industry, finance, telecommunication ...) and efficient to treat problems of classification, shape recognition or function approximation. And it is precisely in this last use that we had recourse to neural networks.

Succinctly, a database, with inputs (independent variables) and target (dependent variable) is presented. The network approximates with a non-linear function the relationship between inputs and targets and can modify this function to minimize the error between the calculated outputs and the targets values [10, 11]. In our study we used a backpropagation multilayer perceptron provided by the Neural Network Matlab Toolbox. This network has nine input neurons (the measured variables), one output neuron (sound pleasantness) and twenty eight neurons in the hidden layer see Figure 5.

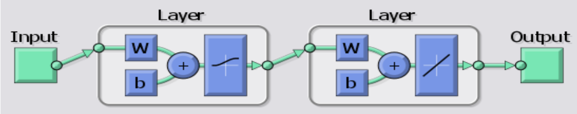

Figure 5. neural network structure

Methodology

In order to compute and test the predictive models we used a cross-validation technique. So, for each location, the database (sixty subjects) was divided into two databases. One to set up the model (construction database) and one to test it (test database). For the neural network model, the first database (30 subjects) was divided into a learning database (12 subjects) and a validation database (18 subjects). The proportion of three databases (learning, validation, testing) may vary depending on use. We chose respectively 50-20-30 %, i.e. thirty subjects for learning, twelve for validation and eighteen for testing [10]. The subjects were randomly assigned to each database.

For each location, ten pairs of databases (construction and test databases) were randomly selected. For each one, a multiple linear regression model was performed. Therefore we obtained the regression equation and two determination coefficients (targets vs. outputs), one for the construction database (Rc^2) and one for the test database (Rt^2).

Concurrently, we ran 10 neural networks where the output value should range between 0 and 10 (ANN without criteria in table 4). We also ran another 10 neural networks with the objective to have a better Rc^2 and Rt^2 than the multiple linear regression (ANN with criteria in table 4).

RESULTS

For each location, we report below the best of the ten selected databases, i.e. the one with the nearest (Rc^2(reg), Rt^2(reg)) to the maximum (1,1).

Location 1 (inside the park)

Using the Statgraphics software, a multiple linear regression model between sound pleasantness and nine explanatory variables was run. The equation of the model is as follows.

S_PL = 3.0 - 0.166*Noi + 0.019*Dyn + 0.028*Env + 0.429*V_PL + 0.132*Fam - 0.313*TP_LV + 0.128*TP_HP - 0.112*TP_Bir + 0.144*Suit (1)

Calculated sound pleasantness (outputs) based on equation (1) is presented in Figure 6 (construction database) and Figure 7 (test database).

Then, Table 4 summarized all results obtained with the neural networks, without and with criteria, and for each one the number of tries needed. Figure 8 is a graphic representation of the Table 4.

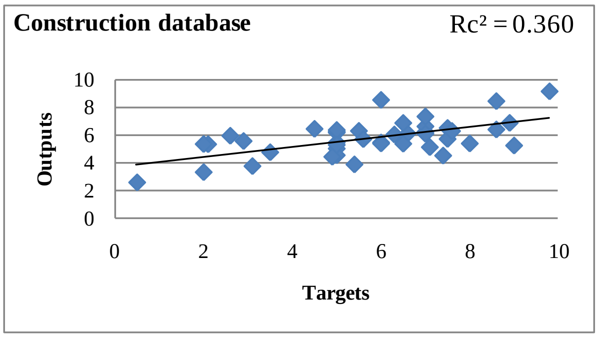

Figure 6. Calculated sound pleasantness (outputs) vs. Measured sound pleasantness (targets) – construction database

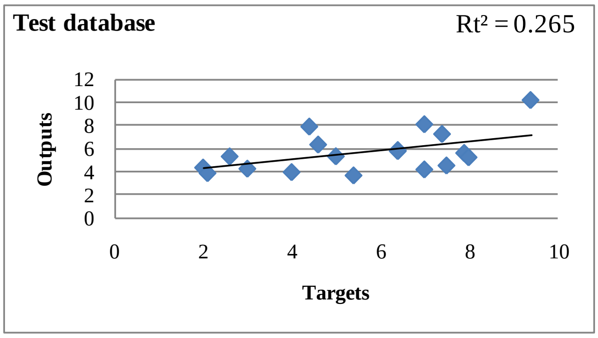

Figure 7. Calculated sound pleasantness (outputs) vs. Measured sound pleasantness (targets) – test database

Table 4. Results for the location 1

Multiple linear regression	Rc^2(reg)	Rt^2(reg)	Tries
	0.360	0.265	1
Neural network without criteria	Rc^2(ann)	Rt^2(ann)	Tries
	0.032	0.000	1
	0.103	0.020	12
	0.138	0.062	6
	0.173	0.108	5
	0.267	0.048	10
	0.388	0.027	27
	0.391	0.065	24
	0.460	0.208	2
	0.595	0.073	16
	0.616	0.418	2
Mean	0.316	0.103	10.5
Neural network with criteria (Rc^2(reg),Rt^2(reg))	Rc^2(ann)	Rt^2(ann)	Tries
	0.420	0.353	61
	0.425	0.280	547
	0.432	0.282	115
	0.433	0.302	252
	0.498	0.289	150
	0.527	0.315	90
	0.577	0.338	335
	0.584	0.299	203
	0.618	0.331	15
	0.655	0.302	93
Mean	0.517	0.309	186.1

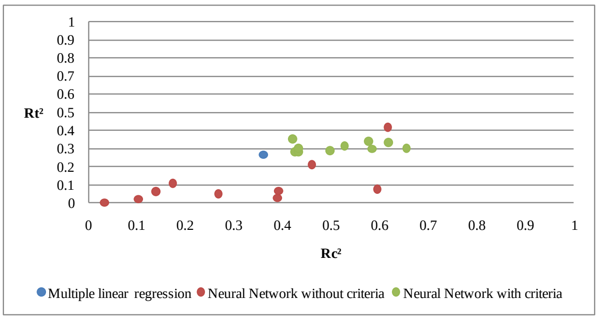

Figure 8. Rt² vs. Rc² for the location 1 (L1)

Location 2 (outside the park)

S_PL = 3.74 - 0.417*Noi - 0.046*Dyn + 0.194*Env + 0.129*V_PL + 0.027*Fam - 0.040*TP_LV + 0.227*TP_TB - 0.080* TP_H + 0.042*TP_HP - 0.167*TP_Bir + 0.215*Suit (2)

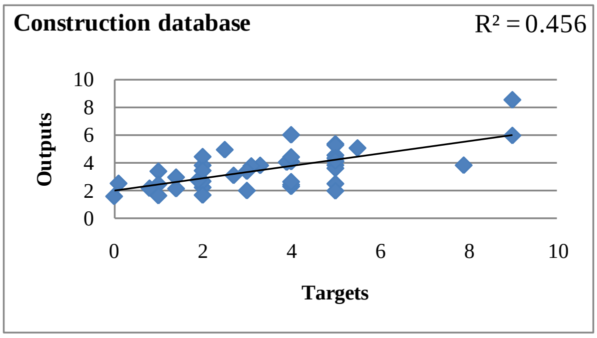

Figure 9. Calculated sound pleasantness (outputs) vs. Measured sound pleasantness (targets) – construction database

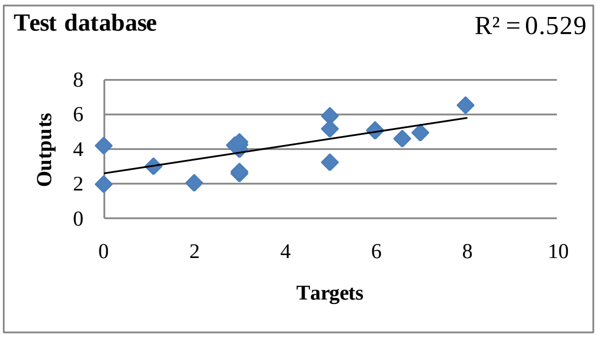

Figure 10. Calculated sound pleasantness (outputs) vs. Measured sound pleasantness (targets) – test database

Table 5. Results for the location 2

Multiple linear regression	Rc^2(reg)	Rt^2(reg)	Tries
	0.456	0.529	1
Neural network without criteria	Rc^2(ann)	Rt^2(ann)	Tries
	0.362	0.029	3
	0.416	0.253	1
	0.458	0.008	3
	0.475	0.144	3
	0.475	0.006	1
	0.512	0.456	6
	0.542	0.004	1
	0.578	0.002	6
	0.707	0.186	7
	0.740	0.071	1
Mean	0.526	0.116	3.2
Neural network with criteria (Rc^2(reg),Rt^2(reg))	Rc^2(ann)	Rt^2(ann)	Tries
	0.581	0.552	447
	0.590	0.582	1853
	0.614	0.586	859
	0.616	0.588	91
	0.629	0.551	714
	0.658	0.606	1700
	0.697	0.555	84
	0.699	0.538	472
	0.720	0.578	2080
	0.832	0.648	250
Mean	0.664	0.578	855.0

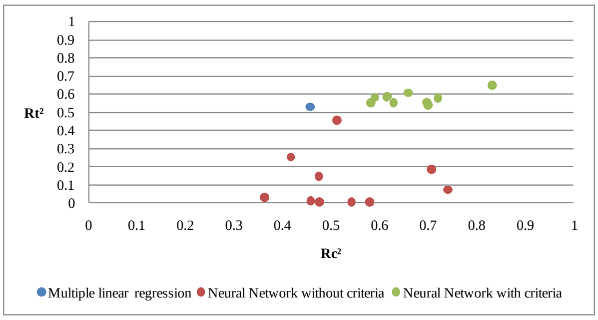

Figure 11. Rt² vs. Rc² for the location 2 (L2)

Discussion

In order to find a sound pleasantness descriptor, multiple linear regressions allow variable importance to be understood. Concerning equations (1) and (2), noisiness takes logically an important part in the sound pleasantness explanation but the visual pleasantness and the familiarity are also present. Some remarks can be made regarding sound sources. Sound pleasantness decreased with increasing light vehicles number. Yet the presence of birds has a negative influence. So, in a next study we have to focus on the regression models using stepwise methods.

Concerning neural networks, it is interesting to notice that when there are no criteria, the results are often lower than those obtained with multiple linear regressions (Figure 8,

Figure 11). However, by setting criteria, the neural network is always able to find a better result, but with longer learning steps. For example, for the location 1, due to chance the best results ($Rc^2 = 0.616$; $Rt^2 = 0.418$) were found quickly and without criteria but for the location 2 it took 250 tries to get the best results ($Rc^2 = 0.831$; $Rt^2 = 0.648$).

CONCLUSION

The main purpose of this study was to build urban sound quality predictive models based on perceptive measures through multiple linear regressions and artificial neural networks and to compare both. This research has allowed highlighting the importance of context and expectations to explain the assessment of soundscape quality as it had already been said in different works [4, 12]. New studies on multiple linear regressions should confirm the fact that soundscape quality assessment is very influenced by context [13].

Concerning the prediction, this study showed the advantages of artificial neural networks over multiple linear regressions. Although they can be seen as black boxes, they are more efficient in terms of prediction.

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