Machine Learning Applied to Acoustic Insulation Analysis in Residential Buildings – Part 2: Vertical partitions.

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ABSTRACT

The use of Machine Learning (ML) tools has grown a lot in several areas, including in the civil construction space. Part one of this study tried to use ML to estimate results for sound insulation of floor systems and had concluded that ML is not applicable to those situations. Part two tried some adjustments to the ML script and used an on-site vertical partition system test database as input with ML tools used to estimate new results based on the input data. The conclusion of this new study is that the tool is now more applicable to floor systems but it is not the best form to predict the results, given the complexity of sound propagation between rooms, which is not considered in the statistical analysis of the machine.

1. INTRODUCTION

The use of Machine Learning (ML) grows every day in different areas of life. On one hand, the application of this technology in some areas of life is rife with controversy. On the other hand, the application of ML in research has become more common and presents positive influences. Applied to civil construction and specially in the field of acoustics, this methodology is used only for specific analysis.

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According to Rocha [1] ML is a type of artificial intelligence. Mohri et al. [2] defines ML as a computational method that uses some database of experiments to make predictions and simulations to solve complex problems that are difficult to solve with mathematical models. Rocha also explains the process on a more didactic way: “the algorithms use a set of data as input, pre-processed or not, learn identifying patterns with the data and provide information as outputs that can assist in decision making.”

The ML methodology used in the civil construction space has a special use for damage detection in bridges and buildings [1,3-5]. In the acoustics field, the study of Campos et al. [6] uses ML to identify different types of vehicles in videos of highways and roads and use this information to elaborate noise maps with more agility and accuracy. In another sub-field of acoustics, ML has also been used for the recognition of emotion in speech in audio [7].

At the same time, acoustics consultants in Brazil find it still very usual for clients to have doubts related as to why a single composition is suitable for a building, but not for another. For that matter, the part 1 of this study [8] had the goal of evaluating the applicability of the ML tools for the prediction of acoustical isolation for floor systems in residential buildings. The results showed that it is not possible to estimate the results of the acoustic insulation to guarantee the important decision making. The present study uses the same methodology with some improvements for the prediction of acoustical isolation in vertical systems in residential buildings.

To better understand the study, Section 2 presents the functioning of the ML methodology applied in the study. In Section 3, the database used will be presented and the interaction between the ML and the data and variables of it. Section 4 presents the obtained results and brings other conclusions from the authors regarding the subject.

2. MACHINE LEARNING

There is a classification system for ML algorithms. For example, Ayodele [9] uses the classification according to the type of learning that is categorized into six groups. The present study uses supervised learning that is suitable for cases in which the database for machine training is complete and has the correct answers for the problem to be solved.

The algorithm collects or defines a complete database that contains all the variables and the correct answer to each item. This database is pre-processed to identify outliers and to verify the quality of data. A part of the database is used for the training stage: with this part, the machine will understand the problem. Another important objective of this stage is the identification of the relation between each variable with the variable in question, which is the answer to be solved by machine.

The other part of database will be used for the test of the algorithm, in order to verify the machine’s accuracy to solve that problem. If the accuracy is not reasonable, it is necessary to make improvements to the algorithm to try to obtain better results. Some examples of these improvements are the verification of the database to remove outliers and the use of a bigger portion of the database for the training part. Some other parameters can be modified to seek better results. This process is made until an adequate result is obtained or until it is verified that in fact the problem cannot be solved with this methodology. Ayodele [9] presents the Figure 1 to illustrate all these processes of algorithm based on supervised learning.

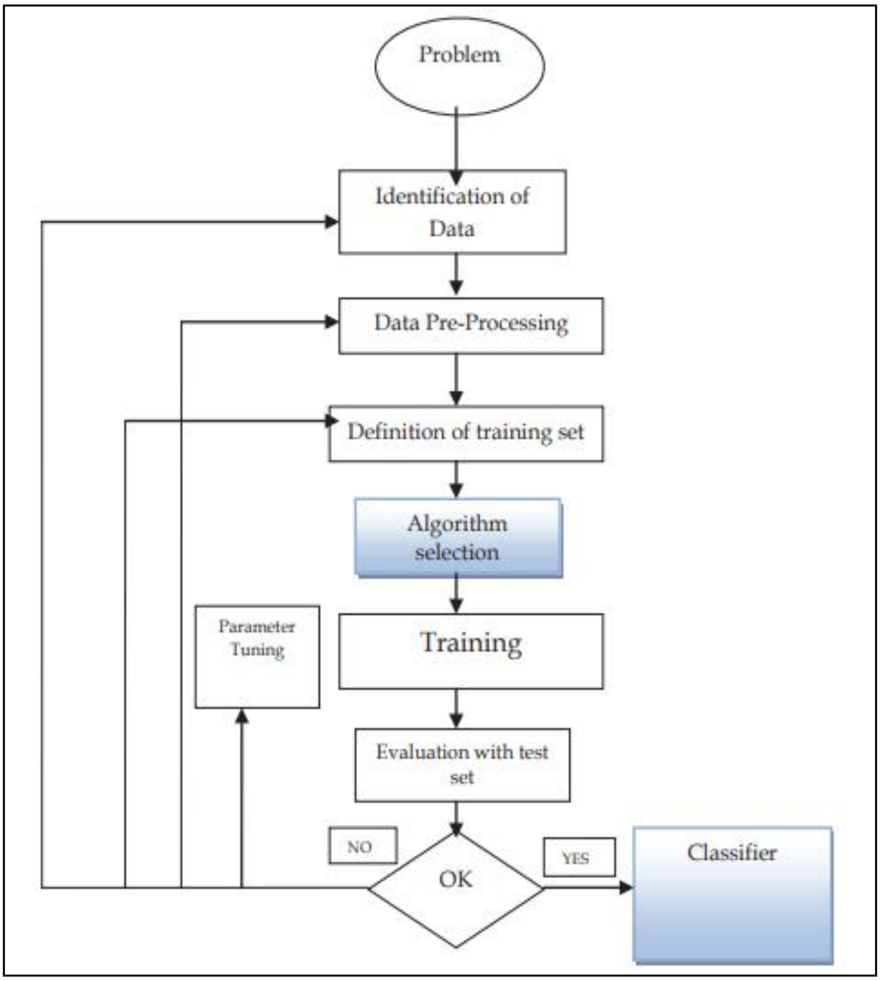

Figure 1: Algorithm's process based on supervised learning [9].

3. METHOD

The database used in this study contains results obtained from field measurements of sound insulation of vertical systems by Giner Acoustics' measurement lab. Such measurements were carried out according to the ISO 16283-1 [10] regulation and processed according ISO 717-1 [11] for evaluating the airborne sound insulation given by the Weighted standardized level difference DnT,w.

The database contains more than 140 samples of measurements of airborne sound insulation of a vertical system. Measurements include room geometric characteristics such as the source and receiver room volumes and areas of common partitions. The majority of data, however, is relative to the tested composition: type of system, thickness, existence or not of a wall lining (without its composition) and type and thickness of the finishing elements.

Five system types were defined: 1 for drywall, 2 for ceramic block, 3 for masonry block, 4 for structural masonry and 5 for a hybrid composition with masonry with drywall lining. Five finishing elements were also defined: 0 for no finishing, 1 for gypsum, 2 for mortar, 3 for mortar plus ceramic and 4 for ceramic.

The objective of this study was to verify if the ML algorithm would be able to classify a system based on its characteristics and room geometry in accordance to the Brazilian performance regulations ABNT NBR 15575:2021 [12], presented in Table 1. Only the results in accordance to the "Minimal" and “Intermediary” specifications were considered, given the small number of results in accordance to the “Superior” specification.

Table 1: Results classification according to ABNT NBR 15575:2021 [12].

Single-number quantity	Reference value	Category
Airborne sound insulation DnTw	< 45 dB	Not in accordance
	45 to 49 dB	Minimal
	50 to 54 dB	Intermediary
	≥ 55 dB	Superior

Table 2 summarizes the information from the database and the problem’s variables, in which it is possible do identify the presentation form of the data of each variable.

Table 2: Summary of the variables indicated in the database.

Single-number quantity	Filling format
Volume of the source room	In m^3
Volume of the receiving room	In m^3
Partition area	In m^2
System type	1 to 4, according with the type
Wool panel	0 if non-existent; 1 if existent
Total thickness	In mm
Quantity of plasterboards	Unity
Finishing elements type	0 to 4, according with the type
Finishing elements thickness	In mm
Masonry filling	0 if non-fill; 1 if fill
Generic acoustic products	0 if no; 1 if yes

The algorithm was coded in Python using the Scikit-learn library developed for supervised ML. A specific function in this library separated the database between training and testing datasets automatically and randomly. The data values were normalized with this function to guarantee that the ML made a correct verification of the weight of each variable.

After the training stage, a test was made with the remainder of the database to validate the accuracy - the percentage of right answers related to the database response itself - for each classification. After analyzing the values, adjustments were made in the algorithm to achieve effective models for the problem resolution. The GridSearch technique was used in this study to optimize and automate the definition of the above parameters**.** The best division between a training set and a test set, for the studied situations, was 75% and 25% of the analyzed database, respectively.

4. RESULTS AND CONCLUSIONS

Initially, to identify outliers and obtain a better and deeper understanding of the problem in question, the correlations between the variables and the obtained results were analyzed as shown in Figure 2. Each different color represents one of the results: purple for not in accordance to ABNT NBR 15575:2021; blue for in accordance with the “Minimun” requirement; green in accordance with the “Intermediate” requirement and yellow for in accordance with the “Higher” requirement. One more time it is important to say that the results for the accordance to the “Higher” requirement are not included on ML analysis, but it makes part of the data base. Because of that, this sample is shown in Figure 2. The last part of the image corresponds to the histogram of the data: it is possible to identify that most of the data present results of DnTw between 40 to 50 dB.

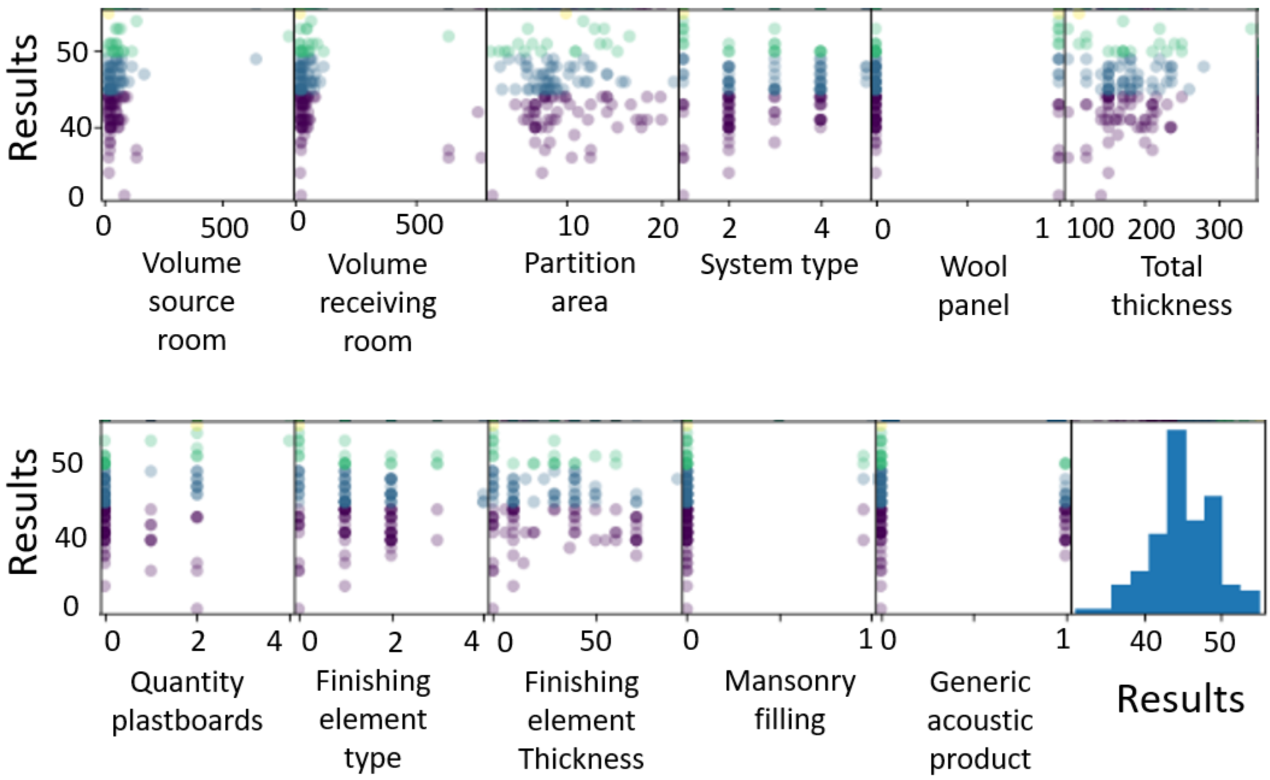

Figure 2: Correlation between parameters and results of samples.

Despite being almost obvious, it is important to make some observations about the correlations: as the volumes of the source and receiving rooms grow, the more likely it is to obtain better results. The same happens with the increase of the total thickness, and it is possible to see that, with the increase of the thickness, the less the incidence of not in accordance to and of the “Minimum” requirement.

In the same way, in systems with masonry fillings and with generic acoustics products, few are the cases that do not meet the requirement of the regulation for airborne sound insulation. On the other hand, some type of materials, like the hybrid masonry plus wall lining, is in accordance with the Brazilian regulation on all cases. Another important point to be mentioned is that the type of finishing element is more correlated with the obtained results than with the thickness of these elements.

The results of the testing stage show the best values of accuracy for the classification of intermediary performance: 85%. For the classification of not met and minimal, the values of correctness are 55% and 65%, respectively.

It is worth to mention that, in case of being in accordance or not with the regulation, for example, in case it was needed to take some decision according to the results in this model of ML, the statistical probability of right answers in this decision making would be similar if a coin was tossed. This same reasoning was verified for all cases for impact sound insulation and for the accordance with intermediary for airborne sound insulation in the part one of this study [8]. The existence of some elements, like wall linings, masonry fillings and acoustic products, in most of the cases, guarantee the compliance to the “Minimum” requirement.

With the results obtained, we conclude that it is possible to guarantee an accordance to regulation ABNT NBR 15575:2021 [12] only with the analysis of the data. However, it is very likely that the acoustic solution would be super-dimensioned, and consequently, expensive. Still, it is relevant mentioning that, for the problem in question of the estimation of field sound insulation, there are better methodologies, and even regulated ones, that give more reliable results, like for example the implementation of calculations presented at ISO 12354:2017 [13].

It is clear, however, that other models can be developed with more variables to take into consideration the items not identified in this study, like for example the sealing material of the room's vertical systems. Still, studies with bigger databases may present better results, although the use of this type of estimate is not justified, considering the existence of more suitable and assertive methodologies for this type of prediction, as already addressed in this article.

In conclusion, by using the methodology applied in this study and with the database used, it is not possible to estimate the results of the acoustic insulation in order to guarantee the important decision making. However, the results are generally better for this analysis than for floor systems, as demonstrated in part one of the study [8].

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