

## MACHINE LEARNING APPLIED TO ACOUSTIC INSULATION ANALYSIS IN RESIDENTIAL BUILDINGS

PACS: 3.58.Ta; 43.55.Ka; 43.50.Yw; 43.55.Ti.

Fengler, Bárbara<sup>1</sup>; Rocha, Raquel Rossatto<sup>2</sup>; Giner, José Carlos<sup>3</sup>

<sup>1</sup>Giner - Designing Sound Spaces, São Paulo, Brasil, barbara@giner.com.br

<sup>2</sup>Giner - Designing Sound Spaces, São Paulo, Brasil, raquel@giner.com.br

<sup>3</sup>Giner - Designing Sound Spaces, São Paulo, Brasil, jcginer@giner.com.br

**Keywords:** measurements, acoustic performance, machine learning, prediction

### ABSTRACT

The use of Machine Learning tools has grown a lot in several areas, including civil construction. This study intends to understand whether these tools are applicable for acoustic insulation performance analysis. To reach this goal, the study used as input an on-site flooring systems test database (both for airborne and impact sound) and ML tools were used to estimate new results, based on the input data. The conclusion is that the tool is not applicable in the studied case, given the complexity of sound propagation between rooms, which is not considered in the statistical analysis of the machine.

### RESUMO

A utilização de ferramentas de Machine Learning (ML) tem crescido bastante em diversas áreas, inclusive na construção civil. Pensando nisso, o estudo busca entender se essas ferramentas são aplicáveis para análise de desempenho acústico: a partir de um banco de dados de ensaios in loco de sistemas de piso (ruído aéreo e de impacto) foram utilizadas ferramentas de ML para estimativa de novos resultados com base nos dados de entrada. Conclui-se que a ferramenta não é aplicável no caso estudado, diante da complexibilidade da propagação sonora entre ambientes, a qual não é levada em consideração na análise estatística da máquina.

### 1. INTRODUCTION

Machine Learning (ML), according to Rocha [1], is a ramification of artificial intelligence. The term is defined by Mohri *et al.* [2] as a computational method which uses experience to improve the performance or make precise predictions, usually applied to complex problems that are hard to model mathematically. Rocha also explains the process didactically: “the algorithms use a set of data as input, pre-processed or not, learn with these data identifying patterns and providing information as outputs that can help in the decision making. “

The use of ML in different areas of knowledge have become more common and presents positive influences. In the environmental acoustic area, the ML has been used, for example, to identify the different type of vehicles in videos of highways and avenues [3]. In this case, the idea is to use the information identified by the ML to elaborate a noise map in an effective and agile way. Additionally, the study of dos Santos, dos Reis and Masiero [4] studies the application of these tools for the recognition of emotion in speech audios.

In the civil construction area, the methodology is used for the detection and classification of infrastructure defects [5], detection of structure damage on bridges [6], construction defects [7], and the monitoring of the structural health of buildings [1].

Alongside, for consultants of the acoustic discipline in Brazil, it is still very usual for clients to have doubts related to the reason why a single composition is enough in a building, but not in another. For that matter, the present study has the goal of evaluating the applicability of the Machine Learning tools for the prediction of acoustical isolation in residential buildings. Still, in case the results are unsatisfactory, it is proven and justified that in fact it is not possible to make extrapolations of results between distinct 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

Ayodele [8] classifies the machine learning algorithms in six categories, according to the type of learning. In this study, the used algorithm is the supervised learning, indicated for cases in which the database for machine training is complete and has the correct answers for the problem to be solved.

Figure 1 presents the algorithm's process based on supervised learning: the first step is to collect or define a complete database, with the variable that must be taken into account by the machine and the right answer to each item. Another extremely important point is the pre-processing of the database, which seeks to avoid data considered outliers and even items with missing information.

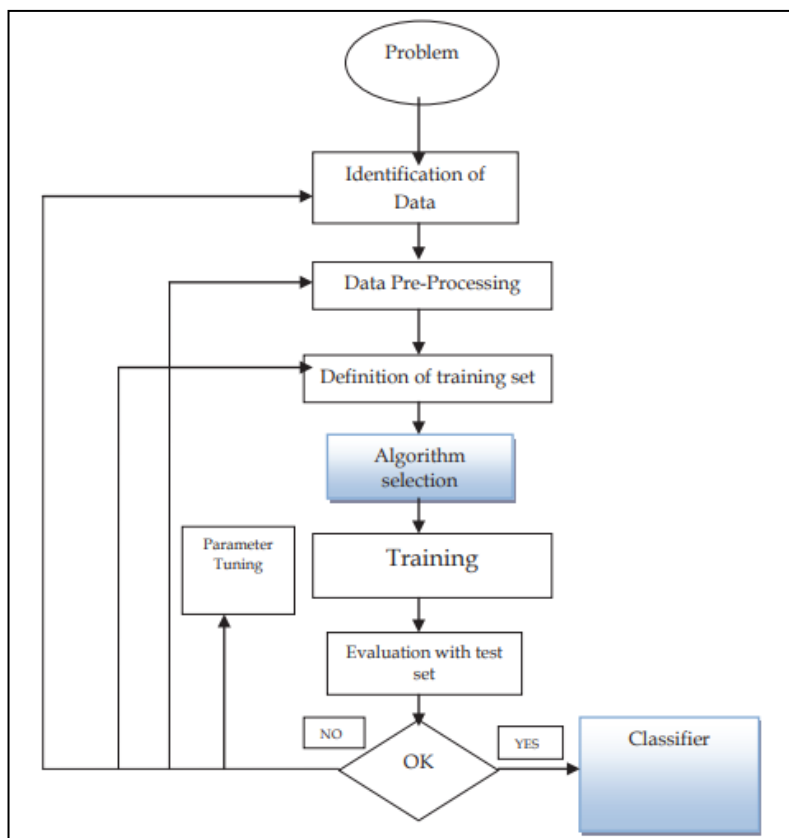


Figure 1 – Algorithm's process based on supervised learning [8].

Part of the database is used for training, with which an algorithm will be applied on and the machine will be able to understand the problem and the relation between results and variables. The remaining part of the database will be used as a test, in order to verify the machine's accuracy for that problem. In case the results are unsatisfactory, it is possible to use a bigger part of the database for training and evaluate the database again in order to identify outliers that are disrupting the machine's learning. This process is made until an adequate result is obtained or until it is verified that in fact the problem cannot be solved this way.

### 3. METHOD

The database used in this study brings results obtained in field measurements of sound insulation carried out by the company Giner over at least five years. The tests were carried out according with the regulation ISO 16283-1 and ISO 16283-2 for evaluating the airborne sound insulation given by the Weighted standardized level difference  $D_{nT,w}$  and the impact sound insulation given by the Weighted normalized impact sound pressure level,  $L'_{nTw}$ , respectively.

The database used presents more than 150 samples of measurements of airborne sound insulation and 300 samples of impact sound insulation. Amongst each item's data, the rooms' geometric characteristics are indicated, such as the source and receiver rooms' volume and the area of the common partition. Most part of the data, however, is relative to the tested composition: slab thickness; resilient material thickness, if existent; screed thickness, if existent; existence or not of a ceiling, without the indication of composition of it in case it exists; and finishing elements type and thickness.

Note that in the database of the present study only the systems with solid concrete slabs were considered, in order to homogenize the evaluated systems. The finishing elements were separated into seven types, with the value 0 for systems without finishing; 1 for resilient rubber finishing, but without screed; 2 for rubberized concrete; 3 ceramic covering; 4 laminate covering; 5 wood covering; and 6 vinyl covering.

Finally, the results of the problem to be solved: values obtained from the measurement and the accordance or not of the regulation requirements of Brazilian performance ABNT NBR 15575:2021 [9], considering the requirements for the situations between distinct units in the case of at least one of the rooms being a bedroom. The classification was carried on in 4 categories, according with the regulation itself, and has its results presented in Table 1.

Table 1 – Results classification according to ABNT NBR 15575:2021 [9].

Single-number quantity	Reference value	Category
Airborne sound insulation $D_{nT,w}$	< 45 dB	Not in accordance
	45 a 49 dB	Minimal
	50 a 54 dB	Intermediary
	$\geq 55$ dB	Superior
Impact sound insulation $L'_{nTw}$	> 80 dB	Not in accordance
	66 a 80 dB	Minimal
	56 a 65 dB	Intermediary
	$\leq 55$ dB	Superior

Summarizing, the information from the database and the problem's variables are described in Table 2, in which is possible do identify the presentation form of the data of each variable.

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

Variable	Filling format
Volume of the source room	in m <sup>3</sup>
Volume of the receiving room	in m <sup>3</sup>
Partition area	in m <sup>2</sup>
Slab thickness	in mm
Resilient material thickness	in mm
Screed thickness	in mm
Covering thickness	in mm
Type of covering	0 to 6, according with the filling used
Ceiling	0 if non-existent; 1 if existent
Ceiling finishing thickness	in mm
Results	in dB
Accordance of the Brazilian standard	Not in accordance; minimal; intermediary or superior

The ML algorithms were programmed in a script language routine Python, with the library and open code Scikit-learn, which is developed specifically for supervised learning machine. By means of a specific function of the Scikit-learn library, the database was randomly separated in two sets: one for machine training and the other for the testing stage.

Due to the different units among the physical quantities of the variables, the data values were normalized in order to make sure the machine is able to make a correct verification of the weight in each result information.

According to the results obtained in the testing stage, the accuracy is analysed, and also the precision of the machine learning for each of the classifications. The accuracy is the percentage of right answers related to the database response itself, whilst the precision is the percentage of actual real cases among those that the machine reports as real.

By having these values, they must be analysed and adjustments must be made in the algorithm so that it is possible to achieve effective models for the problem resolution. In this study, the GridSearch was used, which makes an optimization process for automatization of this definition. The best division between a training set and a test set, for the studied situations, was 85% and 15% of the analysed database, respectively.

### 3. RESULTS AND CONCLUSIONS

Initially, the correlations between the analysed variables and the obtained results were analysed. This analysis was made with the complete database, previously to the separation among training and testing sets. The objective, beyond identifying possible outliers, is to precisely have a better and deeper understanding of the problem in question.

The results from these analyses can be verified in Figures 2 and 3 for the airborne and impact sound insulation, respectively. The last image of each figure corresponds to the histogram of the data, and it is possible to identify that, for airborne, most of the data present results of DnTw of 40 to 60 dB. For impact sound insulation, even though most of the results are in the range of L'nTw between 40 and 60 dB, the data are more well distributed than to airborne sound insulation.

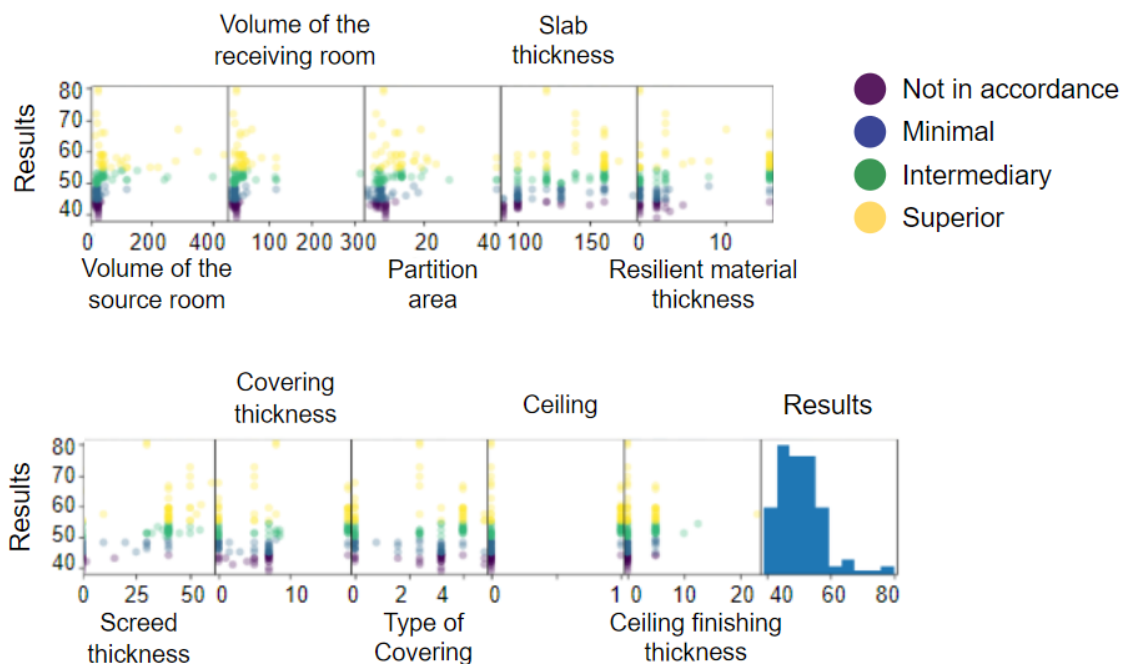


Figure 2 – Correlation between variables and results for airborne sound insulation.

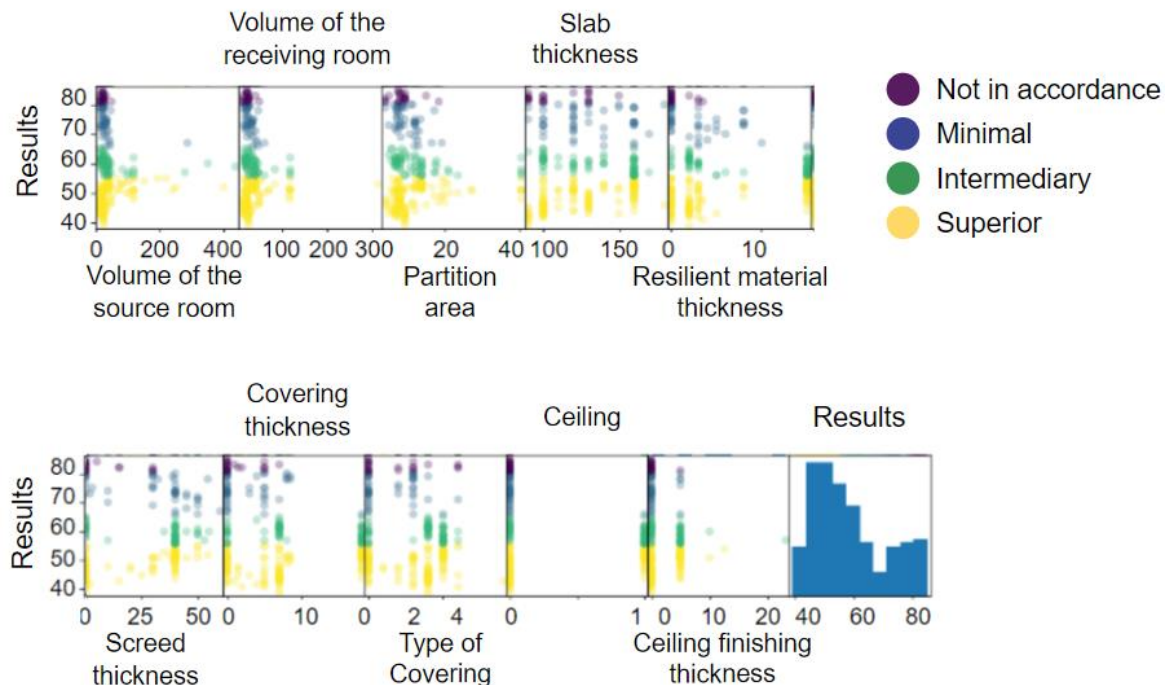


Figure 3 – Correlation between variables and results for impact sound insulation.

By these correlations, some conclusions are already worth mentioning, despite being almost obvious: with the volume growth of the source and receiving rooms, the bigger are the chances of better results, either for airborne sound or for impact sound insulation. The same happens for the increase of the slab thickness, and it is possible to see that, with the increase of this thickness, the less incidence of not in accordance and of the minimal performance. In the same way, in systems with screed, few are the cases that do not meet the requirement of the regulation for airborne sound insulation.

Another important point to be mentioned is that the type of covering is more correlated with the obtained results than the thickness of these coverings, especially in the case of impact sound insulation. When analysing the existence of covering or not, it is possible identify that, when the covering exists, we have the accordance to the airborne sound insulation and the impact in practically all the cases. The same goes to the existence of the resilient material when we analyse the results of the impact sound insulation.

For airborne sound insulation, the results of the testing stage show the best values of accuracy and precision for the classification of superior performance: 77% and 75%, respectively. For the classification of not met, minimal and intermediate, the values of correctness are of 59%, 63% and 41%, respectively.

For the results of the impact sound insulation, the correctness for not in accordance, meeting the minimal, intermediate, and superior are respectively 32%, 14%, 43% and 82%. At the best cases, for meeting the superior performance, the precision found is 76%.

It is worth to mention that, in case of meeting the intermediate performance for airborne sound insulation, for example, in case it was needed to take some decision according to the results in this model of machine learning, the statistical probability of right answers in this decision making would be bigger if a coin was tossed. This same reasoning is also valid for any case of impact sound insulation, except for meeting the superior performance.

With the results, we get to the conclusion that it is possible to guarantee the accordance of the regulation ABNT NBR 15575:2021 [9] only with the analyses of these 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 estimative 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 [10].

The existence of some elements, like ceiling and resilient materials, in most of the cases, guarantee the accordance of the intermediate or superior performance, which explains the bigger correctness of the machine for these cases. This point is especially verified for impact sound insulation, for which the database used is also more representative in the range of meeting the intermediate or superior.

It is clear, however, that other models can be developed with more variables in order 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 database may present better results, although the use of this type of estimative is not justified, considering the existence of more indicated 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.



## ACKNOWLEDGEMENTS

The authors thank to the Giner company for providing the access to the used database in the current research and for the incentive to their team to the development on this and other important issues.

## REFERENCES

- [1] Rocha, L. F. O uso de aprendizagem de máquina para o monitoramento de estruturas da construção civil. Universidade Federal do Ceará, 2021.
- [2] Mohri, M.; Rostamizadeh, A.; Talwalkar, A. Foundations of machine learning., 2018.
- [3] Campos, R. R. E.; Simões, A. B. A. M. R.; Petraglia, M. R.; Torres, J. C. B. Dynamic noise map generation using machine learning. XII Congreso Iberoamericano de Acústica, 2022.
- [4] Santos, A. N. dos; dos Reis, V. A.; Masiero, B. S. Speech Feature Extraction for Emotion Recognition Using Machine Learning. XII Congreso Iberoamericano de Acústica, 2022.
- [5] Feng, C.; Liu, M. Y.; Kao, C. C.; Lee, T. Y. Deep active learning for civil infrastructure defect detection and classification. Computing in Civil Engineering 2017, 2017. p. 298–306.
- [6] Nevez, A.; González, I.; Leander, J.; Karoumi, R. Structural health monitoring of bridges: a model-free ann-based approach to damage detection. Journal of Civil Structural Health Monitoring, Springer, v. 7, n. 5, 2017, p. 689–702.
- [7] Tixier, A. J. et al. Application of machine learning to construction injury prediction. Automation In Construction, v. 69, 2016, p.102-114.
- [8] Ayodele, T. O. Types of machine learning algorithms. New Advances in Machine Learning, IntechOpen, London, 2010.
- [9] Associação brasileira de normas técnicas. NBR 15575: Edificações habitacionais - Desempenho. Rio de Janeiro, Brasil, 2021.
- [10] International Organization for Standardization. ISO 12354 Building acoustics - Estimation of acoustic performance of buildings from the performance of elements. Part 1: Airborne sound insulation between rooms. 2017.