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ACOUSTIC SENSITIVITY ANALYSIS AND MODELING OF SOUND INSULATION PERFORMANCE OF LIGHTWEIGHT WOODEN FAÇADE STRUCTURES

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ABSTRACT: A prediction model is developed based on neural networks approach to estimate the air-borne sound insulation performance of lightweight wooden façade walls. A hundred insulation curves are used to develop the model, and they are lab-based measurements performed on various façades in one-third-octave bands (50 Hz– 5 kHz). For each wall, geometric and physical information (material types, dimensions, thicknesses, densities, and more) are used as input structural parameters. The results are satisfactory, and the model can estimate air-borne sound reduction with acceptable variations. A better estimation is achieved at middle frequencies (250 Hz–1 kHz), while lower and higher frequency bands often depict higher deviations. The weighted air-borne sound reduction index (R_w) can be forecast with a maximum error of 3 dB. In certain cases, the model shows high deviations within fundamental and critical frequencies, which influence the predictive precision. A sensitivity analysis is implemented to investigate on which structural parameters the model relies. The results emphasize the importance of façade thickness and the total density of the clustered exterior layers.

KEYWORDS: Sound insulation, Façades, Artificial neural networks, Sensitivity analysis

1 INTRODUCTION

Wood has been widely used in structural engineering due to its availability in nature and ease of handling [1]. Additionally, it has a remarkably lower carbon footprint than concrete and offers significant thermal insulation. [2, 3]. In Scandinavia and Australia, wooden constructions have become widely popular due to their advantages [4, 5]. Moreover, In North America, wood frame systems were dominant in the building construction industry in the 20th century [6].

Despite the fact that these types of structures reduce both cost and construction time, a disadvantage in these constructions is that the subjective sound isolation quality is considered lower than in concrete or heavy constructions, with the same insulation data [7]. This applies to different lightweight elements, such as floors, roofs, internal walls, and façades. Façade structures are vital to control the indoor acoustic environment by attenuating the outside noise. Inappropriate design may lead to undesirable impact on indoor acoustic comfort for occupants.

However, many façade structures are designed mostly for certain purposes, such as fire safety and thermal insulation, but acoustic aspects are often not considered or misunderstood [8]. The acoustic performance of such structures is derived from standardized measurements, such as

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ISO and ASTM, but it requires time and cost, and the results cannot be generalized to different structures.

A theory-based analytical expression uses stiffness, mass, and damping is utilized as a direct prediction tool known as the mass law [9]. This can be adapted for single-leaf partition, but it is not appropriate for lightweight multi-layered elements. Accurate estimation of the acoustic performance of multilayer structures remains a challenge [9]. Moreover, the standardized method in ISO 12354 Part 1 [10] is extracted using insulation data for heavy monolithic partitions, which is not applicable to lightweight multi-layered structures [11].

The applications of machine learning have paved the way for complex technological achievements in different fields that were considered challenging, such as image recognition, language translation, and building acoustics [12, 13, 14]. In this approach, large and diverse data is essential to enable the algorithm to learn and to improve its predictive power. Artificial neural networks (ANN) approach was used in building acoustics to predict air-borne sound insulation curves in $1/3$-octave bands for masonry walls [14]. 34 laboratory measurements were used to develop the model. Despite the concordance between the results, the study focused on a single monolithic partition.

To bridge this gap, 252 insulation curves of different lightweight wooden floors were used to develop an ANN model [15]. Structural parameters were used as inputs for the model, such as material thickness, density, depth and type of the joists, and more. The model can predict the weighted sound reduction index R_w and normalized impact sound pressure levels $Ln_{n,w}$ with maximum deviations of 2 and 5 dB, respectively.

The scope of this study is to develop an ANN model to estimate the air-borne sound insulation curves of façades structures. The data comprises lab-based measurements of lightweight wooden façades without considering the presence of windows, doors and small openings in the wall. Finally, sensitivity analysis was performed to shed light on the most important factors that influence the prediction of insulation curves.

2 MATERIALS AND METHODS

2.1 DEFINITION OF ARTIFICIAL NEURAL NETWORKS

The ANN model is a mathematical model which is inspired by the human neural system to simulate its behavior [16]. A simple model comprises layers: input, hidden, and output (see Figure 1). Each layer contains artificial neurons (computational units) and intermediate parameters, called weights, connect adjacent layers. The ANN model propagates information (input values) from the first layer (input layer) to the output layer, where prediction values are calculated [17]. The latter process is referred to as the training phase, in which weights and bias values (features of ANN) are tuned in order to reduce errors and achieve higher predictive accuracy. The output of an artificial neuron can be determined by,

$$y = f\left(\sum (w_i x_i + b)\right), \tag{1}$$

where y, w_i, x_i, and b are output, weight, input, and bias values, respectively. The computed output is called activation value, and it is utilized as an input value to the chosen activation function. The most common functions for ANN are tangent, sigmoid, and LeakyReLU [18].

In this study, a multilayer perceptron class of ANN is adapted. The network model comprises two hidden layers. The cross-validation technique is employed to validate the network model and to prevent overfitting issues. As an activation function, LeakyReLU (Leaky Rectified Linear Unit) is chosen for hidden layers [19]. Adam optimizer [20] is employed during the training phase.

Three subsets of measurements are used by splitting the entire curve measurements, namely: training, validation, and test set (Table 1). The root-mean-square error ($RMSE$) function is used as a cost function to evaluate the performance of the network,

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}, \tag{2}$$

where n presents the number of observations (measurements) that are used in the training

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phase. Output (predicted) and input (measured) values are donated by $\hat{y}_i$ and y_i, respectively. In this study, the network model depicted an overall prediction accuracy of 4.44 dB between the predicted and measured curves. However, for a better evaluation of the results at different frequencies, each estimated curve is analyzed with comparison to the measured one using the *RMSE* function considering values in each one-third-octave band from 50 Hz to 5 kHz.

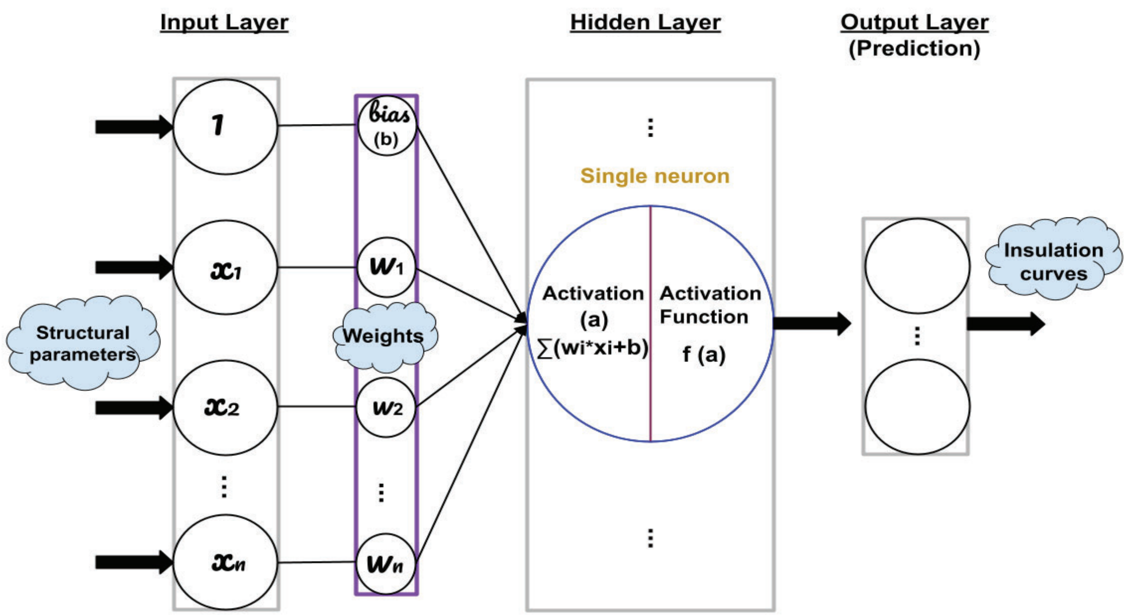

Figure 1: The architecture of an ANN model illustrating input, hidden, and output layers and how the structural parameters propagate through the network model.

2.2 ACOUSTIC DATA

A hundred lab-based measurements were collected from Lund University in Sweden and the National Research Council (NRC-CNRC) [21] in Canada. The data consists of air-borne sound insulation curves that concern various lightweight façade structures in one-third-octave bands (50 Hz to 5 kHz). The measurements were performed respecting ISO 10140-2 (2010) [22] and ASTM E90-09 (2016) [23]. All the insulation data that are performed in compliance with ASTM standards are converted to follow ISO 717-1 (2013) [24] descriptor (the weighted air-borne sound reduction index R_w). This conversion is essential to handle the data and to have a better agreement between them.

The database is organized using different structural parameters (Table 2) that are used as inputs to the network model. Despite the importance of some elastic properties, such as dynamic stiffeners and the modulus of elasticity, they are not considered in the study due to the lack of information provided by the acoustic reports. 10 measurements of different façade walls are used to initiate the features of the ANN model, known as validation set, and another set of 10 curves were selected (randomly from the total number of curves) to test the accuracy of the model (Figure A1 in the Appendix). Each façade configuration is clustered in three parts: interior, main and exterior parts, respecting the installation order of each façade component. The dominant component or material is represented by the main part. Therefore, the interior and exterior sections present components clustered and located alongside the main façade material (Figure 2).

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Table 1: A description summary of acoustic measurements that are used to develop the network model.

	Database	ANN model		
Measurements No.	100	100		
	air-borne	training set	validation set	testing set
	100	80	10	100

Table 2: Structural variables that are utilized to organize the measurements to be used by the ANN model.

Parameter	Unit	Class
– type of material	—	i.e., CLT panel, insulation materials, etc.
– Material installation order	—	first/ second/...
– Material thickness	mm	—
– Group thickness	mm	interior, main and exterior parts
– Total thickness of a façade	mm	—
– Material density	kg/m^3	—
– Group density	kg/m^3	interior, main and exterior parts
– Total density of a façade	kg/m^3	—
– Façade area S	m^2	—
– Volume of the receiving room V	m^3	—
– Studs depth	mm	—
– Spacing between studs	mm	—
– Resilient channels depth	mm	—
– Spacing between Resilient channels	mm	—

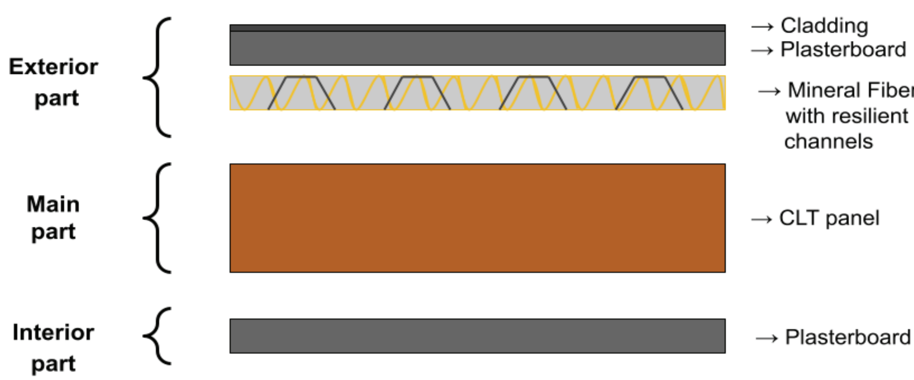

Figure 2: An explanation schematic presenting how façade components are clustered in the database using an example of the test façade #6.

2.3 SENSITIVITY ANALYSIS

Understanding the mechanism of ANN models is cumbersome, especially that they are known as black box prediction tools [25]. To recognize the parameters on which the ANN model relies on,

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an axiomatic approach, called integrated gradients (IG) is adapted. The IG method is defined as $IG_i(x)$. Supposing a function $F : R^n \rightarrow [0,1]$ represents a network model. Using $x = (x^1, ..., x^n) \in R^n$ as an input and $z \in R^n$ as a baseline relative to x. Then a vector $A_F(x,z) = (a^1, ..., a^n) \in R^n$ is the attribution of the input x, where a^i is the attribution of x^i of function $F(x)$. IG values can be extracted by calculating the gradients across the straight path between the input x and the baseline z. Hence, IG for ith dimension is donated by [26],

$$IG_i(x) = (x_i - z_i) * \int_{\alpha=0}^{1} \frac{\partial F(z + \alpha * (x - z))}{\partial x_i} d\alpha. \quad (3)$$

3 RESULTS AND DISCUSSION

3.1 AIRBORNE SOUND INSULATION PREDICTIONS

Figure 3 depicts a comparison between predicted and measured curves. It shows that the estimations are close to the measurements with certain deviations in some cases at high or/and low frequencies. The smallest $RMSE$ value is 2.19 dB for façade #3, and the highest is 5.73 dB for slightly complex wall #10.

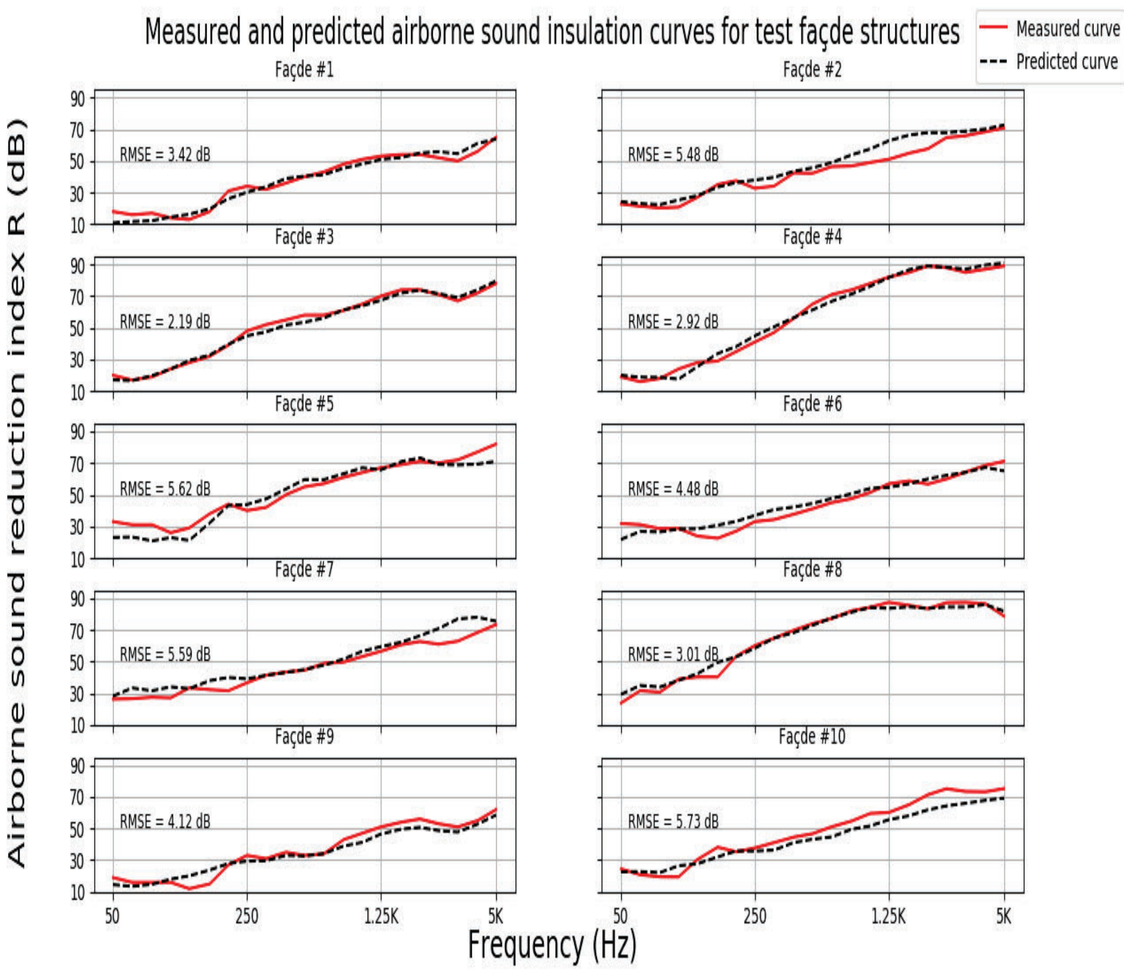

Figure 3: Predicted and measured air-borne reduction index curves for test façades.

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In high frequency bands (1.25–3 kHz), a significant gap is notable between the curves. The later range usually includes the critical (coincidence) frequency for lightweight structures. At these frequencies, a match occurs between the incident wavelength that is projected onto the plate and the wavelength of the bending wave in the plate [9]. As a consequence of this matching, the structure will easily and efficiently radiate sound at and above this range [27].

Furthermore, similar deviations are observed at frequencies lower than 200 Hz, e.g. walls #1, #8 and #9. This can be explained due to the presence of fundamental resonances or first eigenfrequencies [9]. This reveals the limitation of the ANN model in the estimation around these frequencies. Similar challenges were also reported for ANN models [15, 14].

Table 3 presents the RMSE values in the prediction of air-borne sound insulation curves. It also shows the calculated single-number quantities (SNQ), R_w and $R_{wPredicted}$, for each curve. Façade #7 has the highest error with 3 dB, while the network model can estimate the same weighted reduction index values (walls #3 and #6). Additionally, the maximum difference in the calculation of correction terms ($C_{100-3150}$ and $C_{50-5000}$) is 4 dB in façade #5.

Table 4 summarizes the distribution of errors in estimation of insulation curves using $RMSE$, and taking three frequency ranges into account: low (50–200 Hz), middle (250 Hz–1 kHz) and high (1.25–5 kHz) frequency. The results showed that the model accuracy is the best in the middle frequency, while higher deviations are found in low and high frequency ranges. Again, this can probably be described due to the presence of resonance and critical frequencies.

Table 3: Predicted and measured weighted sound reduction indices of test walls.

Façade no.	$RMSE$ **(dB)**	**R**$_w$ **(dB)**	$C_{100-3150}$	$C_{50-5000}$	**R**$_{wPred}$ **(dB)**	$C_{Pred\ 100-3150}$	$C_{Pred\ 50-5000}$
1	3.42	39	−4	−3	40	−3	−3
2	5.48	46	−2	−2	48	−1	−1
3	2.19	53	−4	−6	53	−4	−6
4	2.92	50	−3	−4	51	−6	−6
5	5.62	52	−2	−2	51	−6	−6
6	4.48	55	−4	−4	55	−5	−5
7	5.59	48	−1	−1	51	−2	1
8	3.01	65	−5	−7	67	−4	−5
9	4.12	37	−4	−3	38	−1	−1
10	5.73	49	−3	−3	47	−2	−1

Table 4: Error distributions in the prediction of air-borne insulation curves considering three frequency regions.

	Root-Mean-Square Errors in dB		
Frequency Bands	**Low** **50–200 Hz**	**Middle** **250 Hz–1 kHz**	**High** **1.25–5 kHz**
R (air-borne sound)	4.67	3.52	4.99

3.2 SENSITIVITY ANALYSIS OF FAÇADES STRUCTURAL PARAMETERS

A sensitivity analysis is implemented to investigate the influence of the thickness and density of exterior, main and interior parts of each façade on the forecast. In those types of graphs, a user can find out the importance of each parameter considering the magnitude of $y-$ axis. Higher values indicate a larger size effect of the inputs. However,

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values close to zero suggest a weaker relationship.

Plots in Figure 4 illustrate the contribution of the thickness and density of interior, main and exterior parts of walls to the prediction of insulation curves. It is noticeable that the density and thickness play a significant role at all frequencies. The density spectrum of the interior part illustrates fluctuation near the fundamental frequencies. In addition, the density of the exterior part is vital and the effects of fundamental and critical frequency are obvious on the attributions. A peak near 150 Hz and a dip near 1.25 kHz are obvious, which is probably due to effects of fundamental and critical frequencies, respectively. This is likely resulting due to coupling between resonant wall components that permits energy to transfer between them [27]. The latter happens when elements are physically connected, and they have sufficiently close natural or critical frequencies. This amplifies the radiations from components and affects the isolation negatively [9].

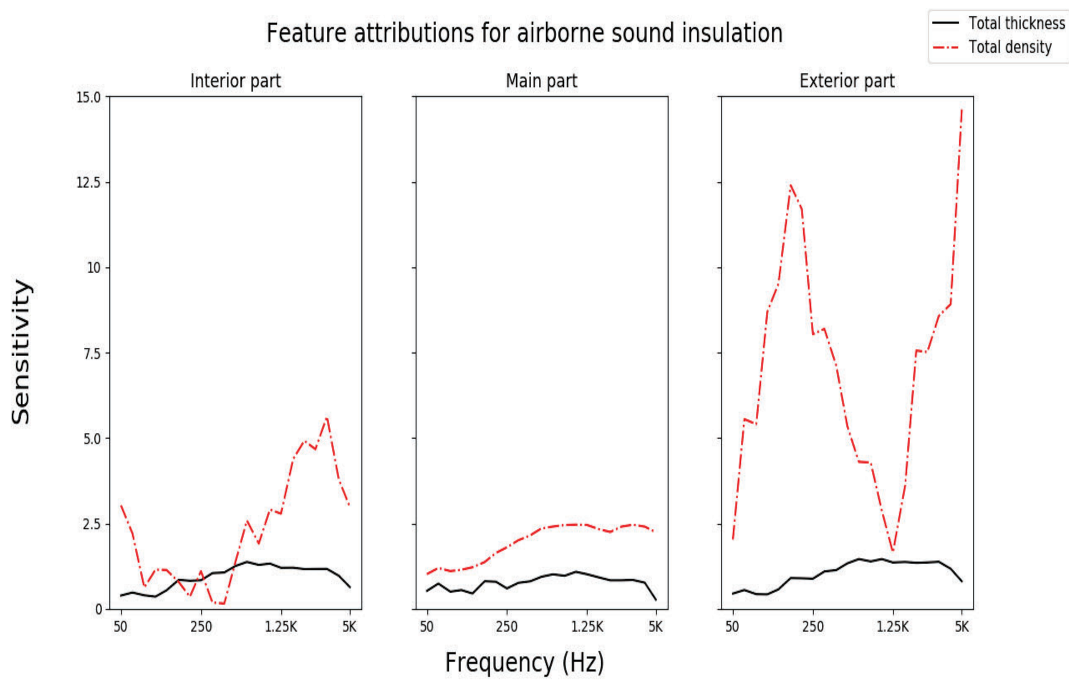

Figure 4: Feature attributions of interior, main and exterior parts façades to the predictions.

4 CONCLUSION

This study reveals the potential of ANN model to predict the air-borne sound insulation curves using 100 lab-based measurements of lightweight façade walls. The results are reasonable, and the model can forecast the sound weighted reduction index R_w with a maximum difference of 3 dB. These results encourage considering the network model in the early design phases, in particular the difference around 2 dB is lower than the noticeable noise differences. Regarding the whole frequency band. The best achieved accuracy is at the middle frequencies (250 Hz – 1 kHz). However, the prediction around fundamental and critical frequency is challenging for the network model and reveals some deviations.

A sensitivity analysis is carried out to explore the attribution of the input parameters to the predictions. The total thickness and total density of interior, main and exterior parts of façades have remarkable effects at all frequencies, and a higher attribution to the total density of the exterior part. The coupling between resonant façade components, resulting from fundamental and critical frequencies of each component, has a significant influence on the prediction.

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Further research would be expected on enlarging the sensitivity analysis study to cover different structural parameters, and how these parameters can be optimized to enhance the sound insulation prediction. This would pave the way to explore the importance of certain structural parameters to achieve the desired isolation.

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REFERENCES IN THE TEXT

[1] Radkau, J. *Wood: A History*; Polity: Cambridge, UK, 2012.

[2] Ottelin, J.; Amiri, A.; Steubing, B.; Junnila, S. Comparative carbon footprint analysis of residents of wooden and non-wooden houses in Finland. *Environ. Res. Lett.* 2021, *16*, 074006.

[3] Bettarello, F.; Gasparella, A.; Caniato, M. The Influence of Floor Layering on Airborne Sound Insulation and Impact Noise Reduction: A Study on Cross Laminated Timber (CLT) Structures. *Appl. Sci.* 2021, *11*, 5938. https://doi.org/10.3390/app11135938.

[4] Jayalath, A.; Navaratnam, S.; Gunawardena, T.; Mendis, P.; Aye, L. Airborne and impact sound performance of modern lightweight timber buildings in the Australian construction industry. *Case Stud. Constr. Mater.* 2021, *15*, e00632. https://doi.org/10.1016/j.cscm.2021.e00632.

[5] Forss*é*n, J.; Kropp, W.; Brunskog, J.; Ljunggren, S.; Bard, D.; Sandberg, G.; Ljunggren, F.; *Å*gren, A.; Hallström, O.; Dybro, H.; Larsson, K.; Tillberg, K.; Sjökvist, L-G.; Östman, B.; Hagberg, K.; Bolmsvik, *Å*.; Olsson, A.; Ekstrand, CG.; Johansson, M. *Acoustics in Wooden Buildings, State of the Art 2008, Vinnova Project 2007-01653*; Report 2008:16, SP Tr*ä*tek; Technical Research Institute of Sweden: Stockholm, Sweden, 2008.

[6] Popovski, M.; Ni, C. *Mid-Rise Wood-Frame Construction Handbook*; FPInnovations: Vancouver, BC, Canada, 2015.

[7] Rasmussen, B.; Machimbarrena, M. *Building Acoustics throughout Europe Volume 1: Towards a Common Framework in Building Acoustics throughout Europe*; DiScript Preimpresion, S.L.: Madrid, Spain, 2014.

[8] Secchi, S.; Cellai, G.; Fausti, P.; Santoni, A.; Martello, N. Z. Sound transmission between rooms with curtain wall façades: A case study *Build. Acoust.* 2015, *22*, 193–207. https://doi.org/10.1260/1351-010X.22.3-4.193.

[9] Vigran, T.E. *Building Acoustics*; CRC Press: Boca Raton, FL, USA, 2014. https://doi.org/10.1201/9781482266016.

[10] *ISO.12354-1*; Building Acoustics–Estimation of Acoustic Performance of Buildings from the Performance of Elements—Part 1: Airborne Sound Insulation between Rooms. International Organization for Standardization: Geneva, Switzerland, 2017.

[11] Guigou-Carter, C.; Villot, M.; Wetta, R. Prediction method adapted to wood frame lightweight constructions. *Build. Acoust.* 2018, *13*, 173–188. https://doi.org/10.1260/135101006778605424.

[12] Thai, L.H.; Hai, T.S.; Thuy, N.T. Image classification using support vector machine and artificial neural network. *Int. J.*

Inf. Technol. Comput. Sci. 2012, *4*, 32–38. https://doi.org/10.5815/ijitcs.2012.05.05.

[13] Sign-to-speech translation using machine-learning-assisted stretchable sensor arrays. *Nat. Electron.* 2020, *3*, 571–578. https://doi.org/10.1038/s41928-020-0428-6.

[14] Serpilli, F.; Di Nicola, G.; Pierantozzi, M. Airborne sound insulation prediction of masonry walls using artificial neural networks. *Build. Acoust.* 2021, *28*, 391–409. https://doi.org/10.1177/1351010X21994462.

[15] Bader Eddin, M.; Ménard, S.; Bard Hagberg, D.; Kouyoumji, J.-L.; Vardaxis, N.-G. Prediction of Sound Insulation Using Artificial Neural Networks—Part I: Lightweight Wooden Floor Structures. *Acoustics* 2022, *4*, 203–226. https://doi.org/10.3390/ acoustics4010013.

[16] Svozil, D.; Kvasnicka, V.; Pospichal, J. Introduction to multi-layer feed-forward neural networks. *Chemom. Intell. Lab. Syst.* 1997, *39*, 43–62. https://doi.org/10.1016/S0169-7439(97)00061-0.

[17] Nielsen, M.A. *Neural Networks and Deep Learning*; Determination Press: San Francisco, CA, USA, 2015. https://doi.org/10.4249/ scholarpedia.32832.

[18] Sharma, S.; Sharma, S.; Athaiya, A. Activation functions in neural networks. *Towards Data Sci.* 2017, *6*, 310–316.

[19] Xu, J.; Li, Z.; Du, B.; Zhang, M.; Liu, J. Reluplex made more practical: Leaky ReLU. In Proceedings of the 2020 IEEE Symposium on Computers and Communications (ISCC), Rennes, France, 7–10 July 2020; IEEE: Piscataway, NJ, USA, 2020. https://doi.org/10.1109/ISCC50000.2020.9219587.

[20] Kingma, D.P.; Ba, J. Adam: A method for stochastic optimization. *arXiv* 2014, arXiv:1412.6980. https://doi.org/10.48550/arXiv. 1412.6980.

[21] Bradley, J.S.; Birta, J.A. *Laboratory Measurements of the Sound Insulation of Building Facade Elements*; Institute for Research in Construction, National Research Council Canada: Ottawa, ON, Canada, 2000.

[22] *ISO.140-2*; Acoustics–Laboratory Measurement of Sound Insulation of Building Elements—Part 2: Measurement of Airborne Sound Insulation. International Organization for Standardization: Geneva, Switzerland, 2010.

[23] *ASTM.E90-09*; Standard Test Method for Laboratory Measurement of Airborne Sound Transmission Loss of Building Partitions and Elements. ASTM International: West Conshohocken, PA, USA, 2016.

[24] *ISO.717-1*; Acoustics—Rating of Sound Insulation in Buildings and of Buildings Elements—Part 1: Airborne Sound Insulation. International Organization for Standardization: Geneva, Switzerland, 2013.

[25] Smilkov, D.; Thorat, N.; Kim, B.; Viégas, F.; Wattenberg, M. Smoothgrad: Removing noise by adding noise. *arXiv* 2017, arXiv:1706.03825. https://doi.org/10.48550/arXiv.1706.03825.

[26] Sundararajan, M.; Taly, A.; Yan, Q. Axiomatic attribution for deep networks. In Proceedings of the International Conference on Machine Learning, PMLR, Sydney, Australia, 6–11 August 2017; pp. 3319–3328.

[27] Rindel, J.H. *Sound Insulation in Buildings*; CRC Press: Boca Raton, FL, USA, 2017. https://doi.org/10.1201/9781351228206.

5 APPENDIX

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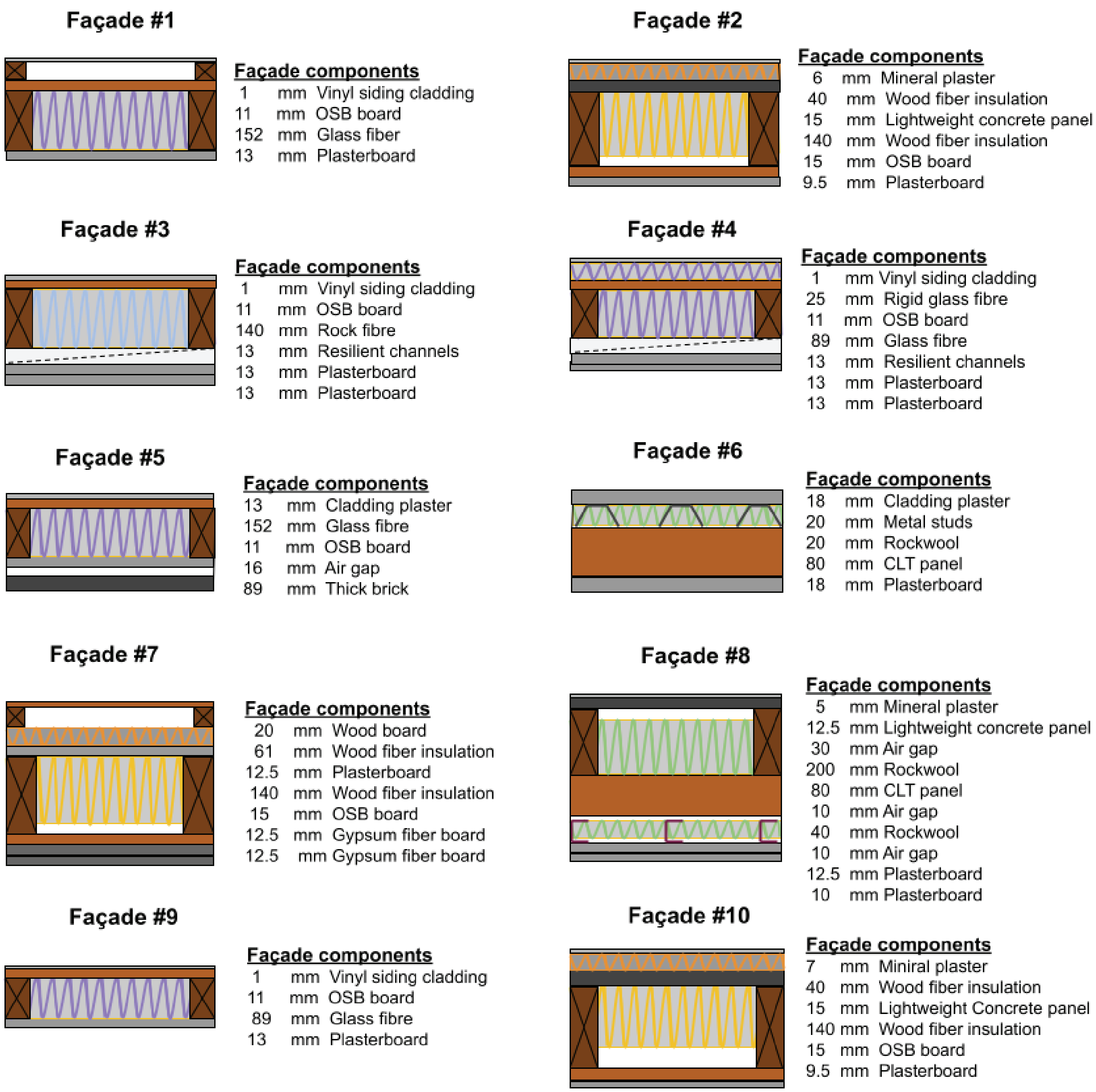

Figure A1: Floor configurations that are used to evaluate the network model for air-borne sound predictions.