Predicting the sound insulation of lightweight frame walls using an artificial neural networks approach

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Introduction

Lightweight frame walls are widely used in construction projects, and they offer many advantages. Besides being lightweight, it is possible to variate the frame types and the panels covering the frame on each side to fulfil the project's needs. The combinations one can build up are nearly infinite since there are so many frame types and panels that can be varied. This is a reason for why prediction tools in acoustics are necessary for lightweight walls so that the sound insulation performance of a specific combination of frames and panels can be estimated.

The literature [1, 2, 3] describes how to calculate the sound reduction of typical lightweight frame walls that are coupled and decoupled. These theories correlate relatively well with measurements for the common frame types. The theories are also applicable to various manufacture products. However, it requires certain assumptions along the way, followed by measurements of the performance of the frame studs. Another alternative would be to develop a prediction model for sound insulation that can calibrate itself based on a few input parameters and measurements.

The artificial neural network (ANN) approach is a type of machine learning method suitable to predict the sound insulation of measurement data. Several papers have previously investigated the positive effects of using an ANN model to predict the sound insulation of lightweight floors and facades [4, 5] with nice results.

This paper aims to investigate if the ANN approach is suitable for lightweight frame walls and to look more deeply into its strengths and weaknesses to be used as a prediction model for the building industry.

Materials and Methods

Artificial neural networks

The ANN approach is an advanced machine learning method that is based on how the organic brain works. A simple ANN model has several layers, including input and output layers, along with hidden layer(s) in between. Each layer consists of several artificial neurons that are connected to every neuron in the next layer [6]. These connections between neurons have trainable weights, w_i, and a bias, b, that are used with an activation function, f, following Equation 1.

$$y = f\left(\left(\sum_{i=1}^{n} w_i x_i\right) + b\right) \tag{1}$$

The input values of the neurons in one layer, x_i, together with weights and a bias, results in an output value, y, of a neuron in the next consecutive layer.

Before simulations take place, a database is first divided into three sets which are training, validation, and test sets. In the training set, the ANN model is shown the actual values for both the input and output layers. In the validation and test sets, only input values are shown for the model and the predictions for the output layer are then used for comparison with the actual values.

The models in this paper consist of three hidden layers, the Adam optimizer, and the LeakyReLU activation function. The models are coded in Python language with the PyTorch machine learning library. Several techniques are employed to minimize overfitting, including weight decay and early stopping. Moreover, after the test data is sorted out, training and validation data are randomized from the remaining measurements so that each run of the model is roughly unique, and this helps make the model less overoptimized.

Database samples and input parameters

This study analyses 8 different wall frame studs. 2 of them are coupled without resilient bars, 2 are coupled with resilient bars, 2 are staggered and 2 are decoupled. Measurements are used from mainly NRC in Canada [7] and LTH in Sweden [8]. In total, 331 measurements are used in this study from the reports and two separate ANN models have been used. The reason for this approach is due to the different behaviours between coupled stud walls and the ones that are staggered and decoupled. A model was first developed for all wall configurations, but the predictions were not in alignment with the targeted values in this study. Thus, two separate models were used with similar settings.

The walls from the measurement reports generally consist of a frame in the middle followed by panels on both sides. The panels vary in manufacturer, thickness, density, and the number of boards per side of the frame. Insulation is used between frame studs for most of the data, where a few are without insulation. The principal build-up is displayed in Figure 1 for two typical wall stud types.

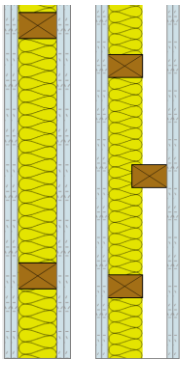

Figure 1: Principal build-up of different walls (wooden coupled studs, left, and staggered wooden studs, right) with panels and insulation. Illustrations from Acoulatis [9].

For each frame type, there are different numbers of measurements used from the reports [7, 8], and this can affect the result accuracy. The number of measurements used for each frame type is displayed in Table 1.

Table 1: Number of measurements for each frame type used from the measurement reports.

Frame type	Number of measurements
Wooden frame studs, fixed	25
Steel frame studs, fixed	93
Wooden frame studs with resilient bar	80
Steel frame studs with resilient bar	15
Staggered wooden studs	38
Staggered steel studs	8
Decoupled wooden studs	44
Decoupled steel studs	28

The input parameters used in the models are displayed in Table 2. The dynamic stiffnesses for three of the coupled wall studs are used from Ref. [10]. For the coupled/fixed wooden stud wall, a value was estimated and thereafter adjusted to correlate with the test data. Moreover, an iterative approach was used to set the dynamic stiffnesses for the staggered and decoupled studs since no data on the dynamic stiffnesses could be found for those configurations.

Table 2: Input parameters used in the ANN models.

Parameter	Unit
Surface density of left layer(s)	kg/m^2
Surface density of right layer(s)	kg/m^2
Dynamic stiffness of the wall studs	MN/m^2
Stud distance (C/C)	mm
Depth of the cavity	mm
Surface density of the insulation	kg/m^2

There are a lot more parameters that could be included compared to what is shown in Table 2. However, after running the model many times, it was found that many parameters resulted in worse results. Parameters that were used in the earlier models were: the number of layers on the left side, the number of layers on the right side, the density and the thickness of the insulation as separate parameters, and the flow resistivity of the insulation.

Results and Discussion

The models were run several times to make sure that the results were similar and corresponded with what is seen in the following figures. The accuracy is relatively constant with some deviations occasionally for a few test measurements. For each frame type, two measurements are used as test data to compare with the predictions from both models. For Figures 2-9, the red solid lines are input/measurement data from the reports [7, 8] along with the weighted sound reduction index. The dashed black curves are predictions from the ANN models, along with the root-mean-square error (RMSE) and the weighted sound reduction index, R_w.

The test data consists of measurements with varying configurations of for example number of panels, stud distance, and density/presence of insulation to cover many variations.

Fixed and resilient frame types (coupled walls)

For the fixed and resilient frame types (the first four frame types in Table 1), results are shown in Figures 2-5.

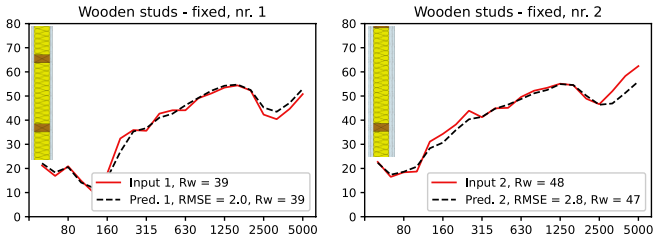

Figure 2: Measurement data compared with predictions from the ANN model for two wooden stud walls, fixed connection.

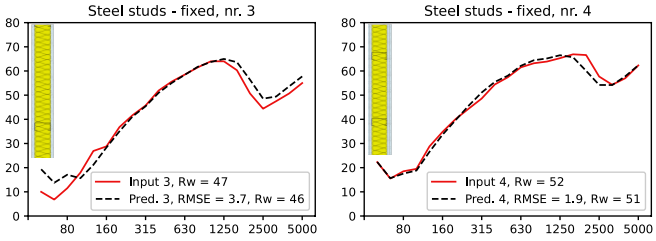

Figure 3: Measurement data compared with predictions from the ANN model for two steel stud walls, fixed connection.

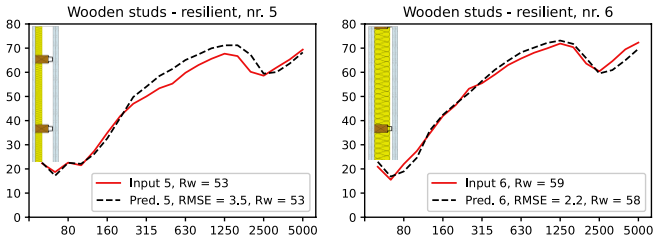

Figure 4: Measurement data compared with predictions from the ANN model for two wooden stud walls with resilient bars on one side.

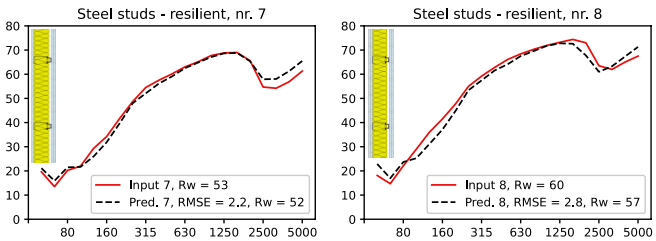

Figure 5: Measurement data compared with predictions from the ANN model for two steel stud walls with resilient bars on one side.

The results for the coupled walls show that the deviation in the weighted sound reduction index, R_w, is typically within ±1 dB, with some minor deviations for specific combina-

tions. The predictions are generally good across the frequency span between 50-5000 Hz. Moreover, both the critical and resonance frequencies are identified for most configurations.

Staggered and decoupled frame types

For the staggered and decoupled frame types (the last four frame types in Table 1), results are shown in Figures 6-9. Please note that nr. 4 is a duplicate of nr. 3 in Figure 7. Only one measurement was used as test data for the staggered steel studs (of 8 possible, see Table 1) to have as many as possible for training and validation.

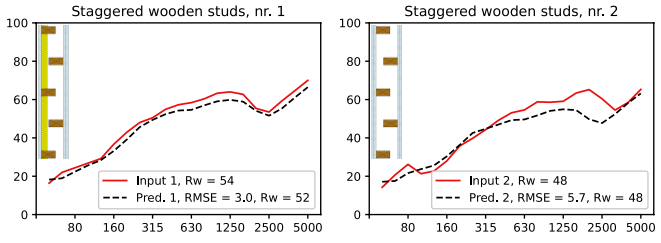

Figure 6: Measurement data compared with predictions from the ANN model for two wooden stud walls, staggared connection.

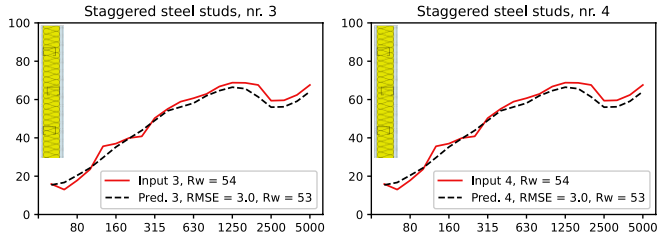

Figure 7: Measurement data compared with predictions from the ANN model for two steel stud walls, staggered connection.

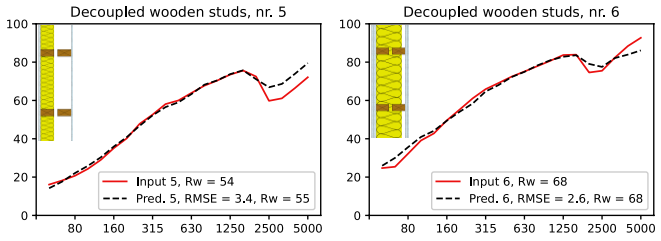

Figure 8: Measurement data compared with predictions from the ANN model for two wooden stud walls, decoupled connection.

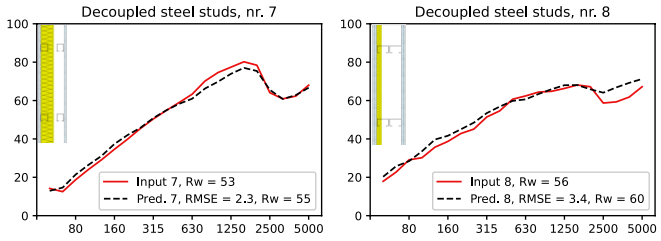

Figure 9: Measurement data compared with predictions from the ANN model for two steel stud walls, decoupled connection.

The results for the staggered and decoupled walls also show that the deviation in the weighted sound reduction index, R_w, is typically within ±1 dB, with some minor deviations for specific combinations. Again, the predictions are generally good across the frequency span between 50-5000 Hz. The critical frequencies are also identified for most test configurations. Somewhat higher deviations are seen for this model, which is clear when comparing the RMSE values between Figures 2-5 and Figures 6-9. However, the deviations are within an acceptable range and the prediction accuracy is generally good.

Sensitivity analysis

A sensitivity analysis was included in the models to understand how much each parameter affects the result depending on frequency. All six parameters were included in the models, and three of them are shown in Figures 10-12 for the decoupled model. In Figure 10, we can see a clear effect of the critical frequency of the panels.

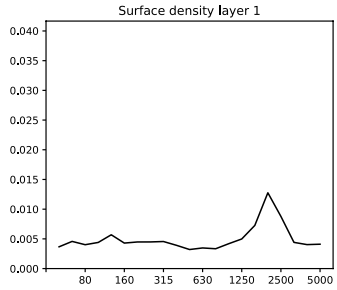

Figure 10: Sensitivity analysis for the decoupled walls ANN model, and specifically the effect of the surface density for the left panel(s).

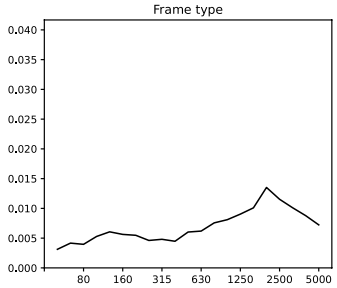

Figure 11: Sensitivity analysis for the decoupled walls ANN model, and specifically the effect of the frame type (dynamic stiffness of the frames).

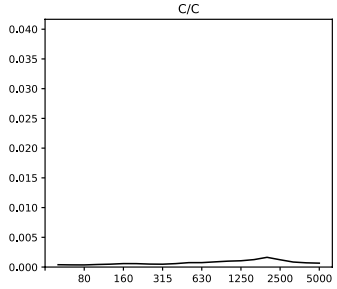

Figure 12: Sensitivity analysis for the decoupled walls ANN model, and specifically the effect of the stud distance of the studs (C/C).

Figure 11 shows the sensitivity analysis for the dynamic stiffness of the frames, and it is positive that the model understands that both the frame type and surface density of the panels have a large effect on the sound insulation. Moreover, the model also understands that the stud distance in Figure 12 has minimum effect, in comparison with the other parameters shown in this paper.

Strengths and weaknesses of the models

The models are, with a few input parameters, predicting the sound insulation with good accuracy both along the frequency spectrum and for the weighted sound reduction index. It is also interesting to highlight that the models predict with good accuracy for frame types where there are only a few measurements used as input. For instance, steel frames with resilient bars and staggered steel studs have the lowest number of measurements per frame stud and the predictions are generally within ±1 dB. In theory, this would mean that manufacturers' frame products could be included in the models to predict the airborne sound insulation, even if they only have a few sound insulation measurements of their frame products.

The ANN models in this paper were developed to be included in the software called Acoulatis [9], which predicts sound insulation of building structures. Initially, when the models were added to the algorithm of Acoulatis, results showed that the predictions were satisfactory for combinations that are similar to what has been seen in the training and validation, which is also found in this paper. However, the models failed to accurately predict the sound insulation for input parameters outside the training and validation range. This is a typical limitation for ANN models used to predict the sound insulation. However, these limitations can be handled by implementing corrections in prediction software to modify inputs and outputs so that they correlate with expected results.

The ANN models in this paper were implemented in a beta-version of Acoulatis together with a correction approach to modify input and output values, and the results show that the predictions yield expected outputs for input parameters that are outside this paper's range, which is good.

Conclusion

The aim of this paper was to investigate if the ANN approach is suitable for lightweight frame walls and investigate if an ANN model can be used as a prediction tool for the building industry.

This paper discloses that an artificial neural network (ANN) approach can be used to predict the sound insulation of lightweight frame studs with good accuracy, based on 331 measurements from several laboratories of eight different frame studs. The root-mean-square error (RMSE) is between 1.9–3.7 dB for the coupled walls and 2.3–5.7 dB for staggered and decoupled walls. For the weighted sound reduction index, coupled, staggered, and decoupled walls are generally within ±1 dB, with some larger deviations for specific combinations of frame types and panels. Moreover, the predictions are generally good over the frequency span between 50-5000 Hz.

Predictions within ±1 dB for the weighted sound reduction index make this approach suitable to be used in calculation tools, and an enhanced model of this approach will be included in the calculation software Acoulatis for further evaluation.

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