Prediction of Sound Insulation of Sandwich Partition Panels by Means of Artificial Neural Networks

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The paper presents the application of Artificial Neural Networks (ANN) in predicting sound insulation through multi-layered sandwich gypsum partition panels. The objective of the work is to develop an Artificial Neural Network (ANN) model to estimate the $R_w$ and STC value of sandwich gypsum constructions. The experimental results reported by National Research Council, Canada for Gypsum board walls (Halliwell et al., 1998) were utilized to develop the model. A multilayer feed-forward approach comprising of 13 input parameters was developed for predicting the $R_w$ and STC value of sandwich gypsum constructions. The Levenberg-Marquardt optimization technique has been used to update the weights in back-propagation algorithm. The presented approach could be very useful for design and optimization of acoustic performance of new sandwich partition panels providing higher sound insulation. The developed ANN model shows a prediction error of ±3 dB or points with a confidence level higher than 95%.

**Keywords:** weighted sound reduction index, $R_w$; Sound Transmission Class, STC.

1. Introduction

The sound transmission through sandwich gypsum constructions has always been a grey area of research for its interior applications for noise abatement and control. There have been many studies (Warnock, 1985; 1990; 1993; 1998; Warnock, Quirt, 1995; 1997; Bradley, Birta, 2001; Bradley, Gover, 2011; Guillen et al., 2008; Uris et al., 1998; Halliwell et al., 1998; Quirt et al., 1995; Roozen et al., 2015) reported so far, especially those reported by National Research Council (NRC), Canada, that focus on the enhancement of sound transmission loss of sandwich gypsum constructions and the use of masonry walls in conjunction with the dry wall technology. Thus, the parametric sensitivity of various factors controlling the sound insulation is instrumental in designing sandwich constructions for optimizing the sound insulation characteristics (Garg et al., 2013a; 2013b; 2013c; 2014a). The method of attachment of gypsum boards via steel studs (staggered, with resilient channels or via double studs), stud spacing, thickness and density of absorptive material used etc. are the pivotal factors affecting the sound insulation. The sound insulation characteristics are shown in terms of single-number rating: Sound Transmission Class (STC) and weighted sound reduction index, $R_w$. Also, there have been various analytical models reported so far for prediction of sound insulation properties of sandwich multilayered constructions (Sharp, 1978; Bradley, Birta, 2001; António et al., 2003; Wang et al., 2005; Pellicier, Trompette, 2007; Garg et al., 2013a; 2013b; Zhou et al., 2013; Garg et al., 2014a; 2015a). Ballax (2004) studies evidently revealed a mean difference in STC/$R_w$ between measurement and theory less than 0.5 dB and 90% of results were found to lie within ±2.5 dB. Kurra (2012) discussed the suitability of three models: Insul SW based on Sharp model with some modifications, Acousys SW using the transfer matrix and windowing technique and FMulay SW based on improved impedance model. Comparison of the calculated data with the experimental data shows that Insul model yields in slightly better compatibility with experimental results, however the correlation coefficients are rather high for all the models. The Acousys and FMulay are capable of calcula-
tions for more complex lagging structures, whereas In
sual is limited to the applications of common building
elements (KURRA, 2001; 2012; Insul (2017); AcouSYS
(2017)). Statistical Energy analysis (SEA) has been
also employed by some researchers to predict the sound
transmission loss through sandwich panels (LYON, DE-
JONG, 1995; CROCKER et al., 1999; CRAIK, SMITH,
2000; WANG et al., 2010). Thus, it is evident from pre-
vious studies that analytical models to a larger extent
have filled the gap between the experimentation and
theoretical predictions and have thus minimized the
necessity of cumbersome and expensive experimenta-
tions required in reverberation chambers. However, in-
spite of all these facts, alternative strategies such as
soft computing skills play a very significant role in pre-
dictions as it has been proven in some previous stud-
ies reported in acoustic field (LIN et al., 2009; NANN-
ARIO, FRICKE, 1999; 2001; NANNARIO et al.,
2001; MUNGIOLI et al., 2006; BURATTI et al., 2013).
BURATTI et al. (2013) developed an Artificial Neural
Network (ANN) model to estimate the $R_w$ value of
wooden windows based on a limited number of window
parameters. A 5-10-10-1 neuron configuration was de-
termined as optimal one with a test RMS error of 2.4%.
The dynamic behaviour of neural networks (NUCARA
et al., 2002; GIVARGIS KARIMI, 2010), capability to
model non linear relationships and flexibility to use any
number of input and output parameters make them
useful for prediction of sound insulation characteris-
tics of multi-layered partition panel constructions. Be-
sides that the analytical models do have certain limi-
tations in prediction accuracy especially in case of mul-
ti-layered constructions.

The present work describes the application of Arti-
ficial Neural Networks (ANN) in modelling sound
transmission characteristics of sandwich gypsum panel
constructions. The sound insulation characteristics of
these constructions are analyzed in terms of widely
used single-number ratings: Sound Transmission Class
(STC) and weighted sound reduction index, $R_w$. Both
quantities are based on shifting a prescribed rating
contour to match the measured values of sound trans-
mission loss versus frequency following rules that spe-
cify the maximum allowed sum of deficiencies below
the contour. For the STC rating, a limit on the max-
imum allowed deficiency below the rating contour in
a single frequency band is also specified (FARK, BRADLEY, 2009).

2. Materials and methods

The present work utilized the experimental results
reported by National Research Council, Canada for
Gypsum board walls (HALLIWELL et al., 1998; QUIRT
et al., 1995). The measurements reported in NRC,
Canada reports (HALLIWELL et al., 1998; QUIRT et al.,
1995) were made in the suite of reverberation cham-
bers in building of the Institute for Research in Con-
struction of the National Research Council, Canada.
The volume of the source room was 65 m$^3$ and that
of adjacent receiving room was 250 m$^3$. The wall test
opening measured 3.05 × 2.44 m. Tests were done in
accordance with the requirements of ASTM E90-1990
and of ISO 140/III 1978 (E). The Sound Transmis-

sion Class was determined in accordance with ASTM
standard classification E413-1987. The number of gyp-
sum layers on either side was one or two, while the
stud types were wood or steel studs. The distance
between studs was varied at two levels: 406 mm and
610 mm on center. The number of resilient channels
was one, two or none and the spacing between the re-
silient channels was varied as 406 mm or 610 mm on
center. The surface density of partition panels tested
varied from 15.6 kg/m$^2$ to 50.23 kg/m$^2$. The sound ab-
sorbing material used was cellulose blown, mineral fi-
bre and glass fibre of varied thickness. 90 mm blown
ceiling of density 49.3 kg/m$^3$ and airflow resistivity
33 000 mks rayls/m was used. The mineral fibre
batt used was 40 mm batt of density 51.9 kg/m$^3$ and
airflow resistivity 15 000 mks rayls/m; 65 mm batt of
density 36.7 kg/m$^3$ and airflow resistivity 11 400 mks
rayls/m and 90 mm batt of density 33.3 kg/m$^3$ and
airflow resistivity 12 700 mks rayls/m. The glass fi-
bre batt used were 65 mm batt of density 11.7 kg/m$^3$
and airflow resistivity 3600 mks rayls/m; 96 mm batt of
density 12.2 kg/m$^3$ and airflow resistivity 4700 mks
rayls/m; 90 mm batt of density 11.2 kg/m$^3$ and air-
flow resistivity 4300 mks rayls/m (HALLIWELL et al.,
1998).

Thirteen input parameters were chosen, i.e.: num-
ber of gypsum layer on one side, number of gypsum lay-
ers on another side, stud type, distance between studs
[mm], sound absorbing material type; sound absorbing
material [SAB] density [kg/m$^3$], sound absorbing
material resistivity [mks rayls/m], sound absorbing material
thickness [mm], thickness of gypsum board [mm], sur-
face density [kg/m$^2$], number of resilient channels, air
gap and spacing between the resilient channels; while
the output parameters considered were STC and $R_w$
exclusively. It may be noted that although the report
shows the sound insulation results for 350 sandwich
partition panel constructions, yet the present study
utilized the data of 283 partition panel constructions
only. This was due to the fact that some sandwich con-
structions don’t fit exactly with the input parameters
as required for developing the ANN model. For in-
stance, some partition constructions had cross brace
between two studs, some had different thickness of
sound absorbing material whereby the properties like
density, air flow resistivity are not clearly mentioned
in the NRC, Canada reports (HALLIWELL et al., 1998;
QUIRT et al., 1995) and as such a uniform database of
283 tested materials only was utilized for developing
an ANN model.
3. Development of ANN model

A neural network consists of interconnected group artificial neurons organized into multiple layers: one input, one or more hidden layers and one output layer. The basic processing elements of neural networks are the artificial neurons. The inputs multiplied by the connection weights (adjusted) are combined and passed through a transfer function to produce the output for that neuron (Ghaffari et al., 2006). The activation function acts on the weighted sum of the neurons inputs. Thus, a neural network is trained to map a set of input data and output data by iterative adjustments of the weights. The most commonly used transfer function is the sigmoid (logistic) function, wherein the activation signal is passed through transfer function to produce a single output of the neuron. The back propagation algorithm used widely trains a given feed-forward multilayer neural network for a given set of input patterns. When each entry of the sample set is presented to the network, the network examines its output response to the sample input pattern. The output response is then compared to the known and desired output and the error value is calculated, based on which the connection weights are adjusted until error reaches a specified level of accuracy. Once the network is trained, tested and validated, it is ready for predictions. The details of the ANN modelling can be found in (Garg et al., 2015b; Zhang et al., 1998; Cai et al., 2009 and Garg et al., 2016). In present study, the data set of sound insulation of sandwich gypsum board partition panel measurements (283 observations) is divided into training data (70%), testing data (15%) and validation data (15%). The multilayer feed forward back propagation (BP) neural network has been trained by Levenberg-Marquardt (L-M) algorithm to develop an Artificial Neural Network (ANN) model for predicting STC and $R_w$ of sandwich multi-layered constructions. A complete representation of all the training data (input and target data) is known as epoch which is repeated until the network reaches a predefined goal of least mean squared error. Trainlm is the network training function that updates weights and bias values according to Levenberg-Marquardt (L-M) optimization. It is often the fastest back propagation algorithm and is highly recommended as a first choice supervised algorithm, although it does require more memory than other algorithms (https://in.mathworks.com). The activation functions used in the learning algorithms for feed forward ANN training play an important role in determining the speed of training (LeCun et al., 1998; Duch, Jankowski, 1999). The logsig activation function used in the present case to introduce non linearity in the model was observed to provide the lowest mean squared error. The training set consists of examples used for learning i.e. fitting the weights for desired output, validation data is used to tune the network parameters and the test dataset is used to assess the performance after leaning (Cai et al., 2009). The number of hidden layers is difficult to decide, but typically no more than one hidden layers is used in a network (Hush, Horne, 1993). The network is run with various trials using different number of neurons in hidden layer. The optimum number of neurons in hidden layer for which the performance criteria, i.e. Mean Squared Error (MSE) and correlation coefficient ($R$) between the measured and predicted data is chosen. The Mean Squared Error is expressed by following equation:

$$MSE = \frac{1}{k} \sum_{p=1}^{k} \delta_{op}^2,$$

where the error $\delta_{op}$ is the difference between the targeted output vector when compared with the neural network simulated vector for $k$ number of training samples. In the case when the MSE is less than the desired error, the neural network training is complete and the network is ready for prediction (Kumar et al., 2014). A program supporting the generalized ANN GUI in MATLAB software has been developed. Thus, the validated network so developed can be used for reliable predictions using the test data set. Figure 1 shows the

Fig. 1. Flow Chart of methodology for development of an ANN Model (Garg et al., 2015b).
flow chart of methodology for development of an ANN Model (Garg et al., 2015b). The learning rate and momentum constant also play an important role in choosing an optimum model. The learning rate defines the size of the changes that are made to the weights and biases at each epoch. Generally, smaller value of learning rate increases the number of epochs and slows down the network convergence but produces better accuracy. Conversely, large value of learning rate leads the network to fast convergence but with less accuracy (Mustafa et al., 2015). The better and efficient convergence depends upon the choice of learning rate coefficient and momentum factor. The other way to improve the convergence with large learning rate is to add momentum factor to the previously changed weights as it smoothens the oscillatory behaviour of weights and leads to efficient rapid learning (Kumar et al., 2014). A high momentum factor can however cripple the network adaptability. Nevertheless, there is no theory that can be used to guide the selection of optimal ANN parameters. The trial-and-error methodology for specific problems is typically adopted by the most researchers which is the primary reason for inconsistencies in literature (Zhang et al., 1998).

4. Results and discussion

Extensive simulations were performed to determine the best combination of parameters involving the network architecture and other parameters such as: learning rate, momentum constant, number of hidden neurons, learning algorithm and activation function. The network was trained with varying the neurons in a single hidden layer from 4 to 20 and each time the MSE and $R^2$ between the measured and predicted data were analyzed. The number of hidden neurons, number of hidden layers, learning rate, and momentum rate were sequentially optimized. Table 1 shows the network parameters used while training the network. An 13:14:1 architecture (13 neurons in input layer, 14 in hidden layer and 1 in output layer) provided the best prediction for the test data set. The optimal learning rate and momentum factor used in developing the ANN model were 0.6 and 0.1 respectively. Figures 2a and 2b show the mean squared error and correlation coefficient of measured versus predicted data for different number of neurons for the ANN model so developed for STC. It is evident that with 14 neurons in the hidden layer, both MSE and $R$ are optimized for testing and training data set. These investigations were repeated by training the network with changing the output parameters as $R_w$, while all other input parameters were kept the same. Training the network with varying number of neurons from 4 to 20 in a single hidden layer reveals that for 14 neurons, optimized performance is sought. Figures 3a and 3b show the mean squared error and correlation coefficient of measured versus predicted data for different number of neurons for the ANN model so developed for $R_w$. Training network with 14 neurons in a single hidden layer shows that the MSE of 1.96 dB(A)$^2$ in training and 7.33 dB(A)$^2$ in testing STC, while a MSE of 1.88 dB(A)$^2$ in training and 6.62 dB(A)$^2$ in testing is observed for $R_w$. The correlation coefficient is observed to be 0.98 in training and 0.89 in testing for STC; while for $R_w$, the correlation coefficient is observed to be 0.98 in training and 0.92 in testing. Thus, the network architecture is finally chosen as 13:14:1 as shown in Fig. 4.

<table>
<thead>
<tr>
<th>Sound insulation parameter</th>
<th>Structure of ANN model</th>
<th>Training algorithm</th>
<th>Activation function</th>
<th>MSE (in dB(A)$^2$ for $R_w$ and points$^2$ for STC)</th>
<th>Correlation coefficient $R$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Training</td>
<td>Testing</td>
</tr>
<tr>
<td>STC</td>
<td>13:14:1</td>
<td>trainlm</td>
<td>logsig</td>
<td>1.96</td>
<td>7.33</td>
</tr>
<tr>
<td>$R_w$</td>
<td>13:14:1</td>
<td>trainlm</td>
<td>logsig</td>
<td>1.88</td>
<td>6.62</td>
</tr>
</tbody>
</table>

Fig. 2. Variation of Mean Squared Error (in point$^2$) and correlation coefficient with number of neurons in a single hidden layer while training for development of an ANN model exclusively for STC predictions.
Table 2 shows the error analysis of developed ANN models for STC and $R_w$. The Root Mean Squared Error (RMSE) observed in both cases is less than 2.0 dB(A) and the coefficient of determination between the measured and predicted data is higher than 0.90, which validates the suitability of the ANN model so developed. Thus, the results showed a good agreement with experimental data for both STC and $R_w$ of sandwich gypsum panels. The scatter plot of measured value of STC and $R_w$ in laboratory and the predicted value from the ANN model developed are shown in Figs. 5 and 6.

![Fig. 3](image1.png)

**Fig. 3.** Variation of Mean squared error (in dB(A)$^2$) and Correlation coefficient with number of neurons in a single hidden layer while training for development of an ANN model exclusively for $R_w$ predictions.

![Fig. 4](image2.png)

**Fig. 4.** Architecture of ANN model developed exclusively for STC and $R_w$.

![Fig. 5](image3.png)

**Fig. 5.** Scatter plot of measured value in laboratory and predicted value of STC from the ANN model developed.

![Fig. 6](image4.png)

**Fig. 6.** Scatter plot of measured value of $R_w$ in laboratory and predicted value from the ANN model developed.

### Table 2: Error analysis of the developed ANN model for sound reduction index and sound transmission class.

<table>
<thead>
<tr>
<th>Sound insulation parameter</th>
<th>Minimum error (in dB(A) for $R_w$ and points for STC)</th>
<th>Maximum error (in dB(A) for $R_w$ and points for STC)</th>
<th>Mean squared error, MSE (in dB(A)$^2$ for $R_w$ and points$^2$ for STC)</th>
<th>Root mean squared error, RMSE (in dB(A) for $R_w$ and points$^2$ for STC)</th>
<th>Mean absolute percentage error [%]</th>
<th>Coefficient of determination $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>STC</td>
<td>-7.0</td>
<td>10.0</td>
<td>3.4</td>
<td>1.9</td>
<td>0.1</td>
<td>0.92</td>
</tr>
<tr>
<td>$R_w$</td>
<td>-6.0</td>
<td>11.0</td>
<td>2.8</td>
<td>1.7</td>
<td>0.3</td>
<td>0.92</td>
</tr>
</tbody>
</table>
The ANN models developed are further validated with the results of paired t test conducted (Table 3) for the predicted and measured single number ratings, STC and $R_w$. In this test, test statistic ($t$-stat) is compared with $t$ critical and if $t$-stat value is within the $\pm t$ critical value for two-tailed test, it reveals that there is no significant difference between the two samples (accept null hypothesis). It is observed that for the ANN model, $t$-stat values are less than and far away from the critical values and are within the non-rejection region, which implies that predicted and measured data fits well (Montgomery, Runger, 2011; Pamanikabud, Vivitjinda, 2002). Figures 7 and 8 show the frequency histogram indicating the frequency (in %) of prediction error, i.e. difference between the measured and predicted STC and $R_w$ for 283 sandwich gypsum constructions. It is observed that for STC parameter, 88% observations show the prediction error of $\pm 2$ dB, while 94.7% observations show the prediction error of $\pm 3$ dB. 27.6% observations show no error between the measured and predicted STC value. Similarly for $R_w$ parameter, 90.8% observations show the prediction error of $\pm 2$ dB, while 98.2% observations show the prediction error of $\pm 3$ dB. 34.6% observations show no error between the measured and predicted $R_w$ value. Thus, it can be concluded that the developed ANN model shows a prediction error of $\pm 3$ dB or points with a confidence level higher than 95%. Also it is evident that the present ANN model shall be helpful for predictions of sound transmission loss properties of multi-layered sandwich gypsum constructions with a reasonable accuracy without experimentation. Future efforts shall be focused on predicting the spectrum adaptation terms and single-number quantities proposed in the extended frequency range of 50 Hz to 5 kHz using ANN modelling as described in the present work (Scholl et al., 2011; Garg et al., 2014b; Garg, Maji, 2015a).

### 5. Conclusions

This paper aims to show an application of the Artificial Neural Networks technique in order to predict the acoustic performance of sandwich partition panels. The output of the developed ANN model is the STC and $R_w$ values of sandwich partition panels. The network was trained and tested on the basis of an experimental database consisting of 283 sandwich gypsum board panels tested at the Acoustics Laboratory, Institute for Research in Construction, National Research Council, Canada. The 13–14–1 neurons configuration was found to be optimal one. The validity of the model so developed is ascertained using statistical tests. The developed ANN model shows a prediction error of $\pm 3$ dB or points with a confidence level higher than 95%. The presented model can be thus applied to design and optimize acoustic performance of new products, by giving the appropriate values for input parameters of sandwich partition panels. The dynamic nature of ANN model thus offers an effective approach for predicting sound insulation properties of sandwich constructions. Undoubtedly, the inclusion of more experimental database of sandwich multi-layered constructions for training the network shall give a more comprehensive model at the price of feeding a more rigorous database. However, despite many advantages,
there are some disadvantages too. Construction of an ANN model depends on the size of training data and network structure and sometimes it is like a black-box wherein one can’t adjudge the weights and biases developed while training the network. However, in spite of these shortcomings, ANN can serve as vital substitute for analytical models for developing sandwich partition panels providing higher sound insulation, thus saving both money and time incurred on experimental testing in reverberation chambers.

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