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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). Ballagh (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 calculations for more complex lagging structures, whereas *Insul* 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, DeJong, 1995; Crocker *et al.*, 1999; Craik, Smith, 2000; Wang *et al.*, 2010). Thus, it is evident from previous 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 experimentations required in reverberation chambers. However, inspite of all these facts, alternative strategies such as soft computing skills play a very significant role in predictions as it has been proven in some previous studies reported in acoustic field (Lin *et al.*, 2009; Nannariello, Fricke, 1999; 2001; Nannariello *et al.*, 2001; Mungiole *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 determined 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 characteristics of multi-layered partition panel constructions. Besides that the analytical models do have certain limitations in prediction accuracy especially in case of multilayered constructions.

The present work describes the application of Artificial 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 transmission loss versus frequency following rules that specify the maximum allowed sum of deficiencies below the contour. For the STC rating, a limit on the maximum allowed deficiency below the rating contour in a single frequency band is also specified (Park, 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 chambers in building of the Institute for Research in Construction 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 Transmission Class was determined in accordance with ASTM standard classification E413-1987. The number of gypsum 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 resilient 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 absorbing material used was cellulose blown, mineral fibre and glass fibre of varied thickness. 90 mm blown cellulose 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 fibre 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 4800 mks rayls/m; 150 mm batt of density 11.2 kg/m^3 and airflow resistivity 4300 mks rayls/m (Halliwell *et al.*, 1998).

Thirteen input parameters were chosen, i.e.: number of gypsum layer on one side, number of gypsum layers 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], surface 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 constructions don't fit exactly with the input parameters as required for developing the ANN model. For instance, 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:

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

where the error δ_{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

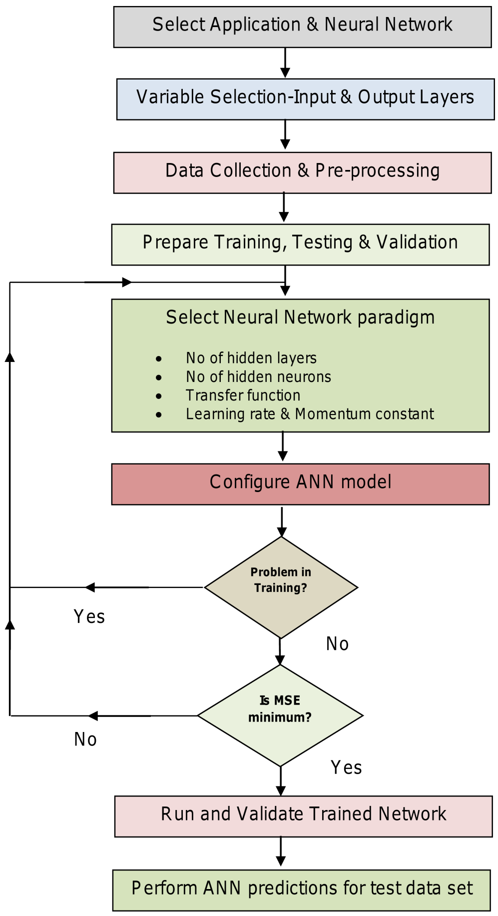

Fig. 1. Flow Chart of methodology for development of an ANN Model (Garg *et al.*, 2015b).

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).

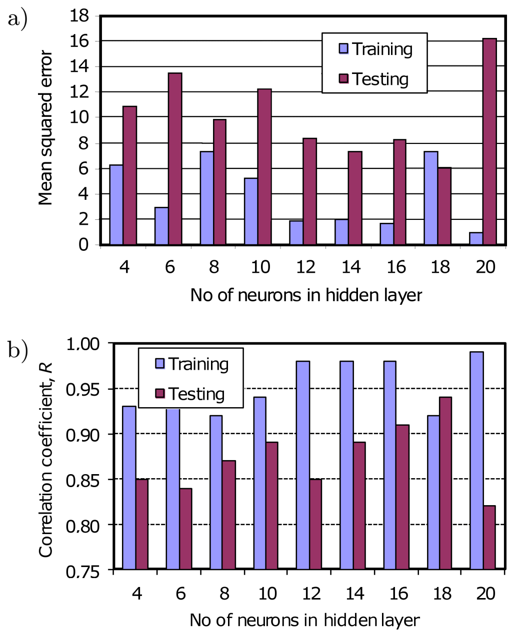

Fig. 2. Variation of Mean Squared Error (in point^2) and correlation coefficient with number of neurons in a single hidden layer while training for development of an ANN model exclusively for STC predictions.

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 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 1. Neural network paradigm used in training.

Sound insulation parameter	Structure of ANN model	Training algorithm	Activation function	MSE (in dB(A)^2 for R_w and points^2 for STC)		Correlation coefficient R	
				Training	Testing	Training	Testing
STC	13:14:1	*trainlm*	*logsig*	1.96	7.33	0.98	0.89
R_w	13:14:1	*trainlm*	*logsig*	1.88	6.62	0.98	0.92

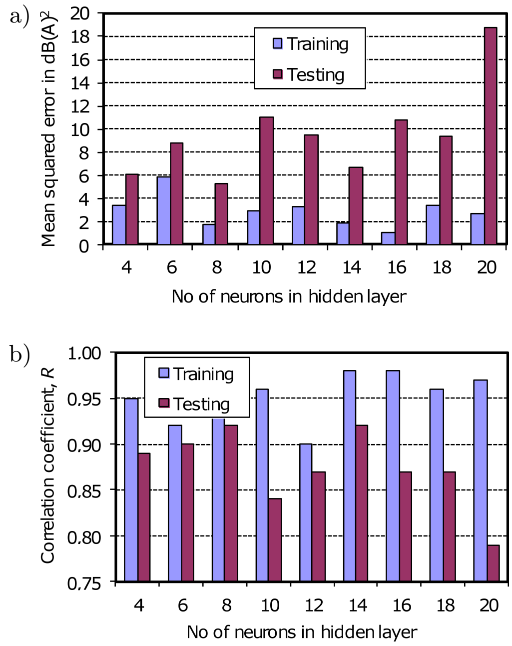

Fig. 3. Variation of Mean squared error (in dB(A)^2) and Correlation coefficient with number of neurons in a single hidden layer while training for development of an ANN model exclusively for R_w predictions.

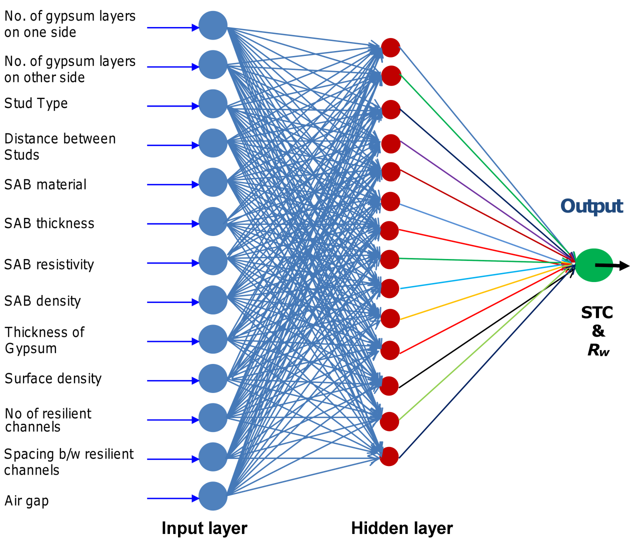

Fig. 4. Architecture of ANN model developed exclusively for STC and R_w.

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.

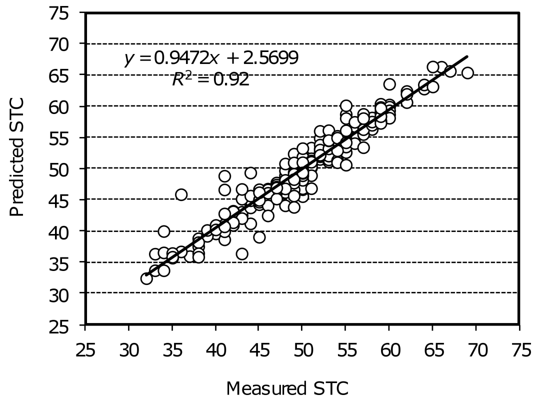

Fig. 5. Scatter plot of measured value in laboratory and predicted value of STC from the ANN model developed.

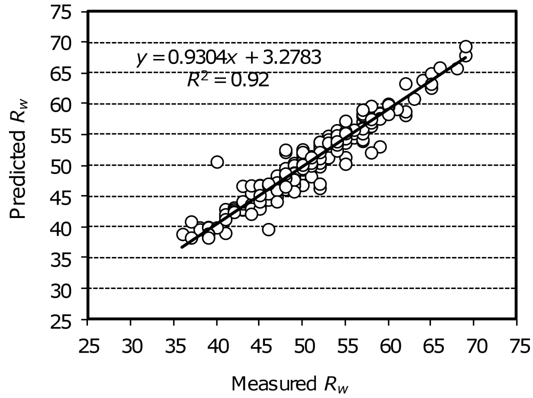

Fig. 6. Scatter plot of measured value of R_w in laboratory and predicted value from the ANN model developed.

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

Sound insulation parameter	Minimum error (in dB(A) for R_w and points for STC)	Maximum error (in dB(A) for R_w and points for STC)	Mean squared error, MSE (in dB(A)^2 for R_w and points^2 for STC)	Root mean squared error, RMSE (in dB(A) for R_w and points for STC)	Mean absolute percentage error [%]	Coefficient of determination R^2
STC	−7.0	10.0	3.4	1.9	0.1	0.92
R_w	−6.0	11.0	2.8	1.7	0.3	0.92

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 ±2 dB, while 94.7% observations show the prediction error of ±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 ±2 dB, while 98.2% observations show the prediction error of ±3 dB. 34.6% observations show no error between the measured and predicted R_w value. Thus,

Table 3. Paired t-test for measured and predicted sound reduction index and sound transmission class.

Statistical parameter	Predicted values from ANN model	
	STC	R_w
Mean absolute error	0.10	0.21
Pearson correlation	0.96	0.96
df	282	282
t Stat	0.40	0.14
P(T <= t) one-tail	0.34	0.23
t critical one-tail	1.65	1.65
P(T <= t) two-tail	0.69	0.38
t critical two-tail	1.97	1.97

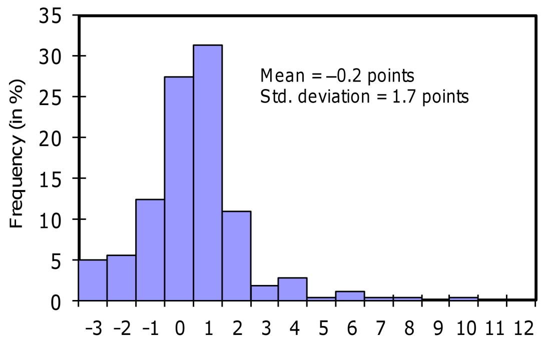

Fig. 7. Histogram showing the frequency (in %) of prediction error, i.e. difference between the measured and predicted STC for 283 sandwich gypsum constructions.

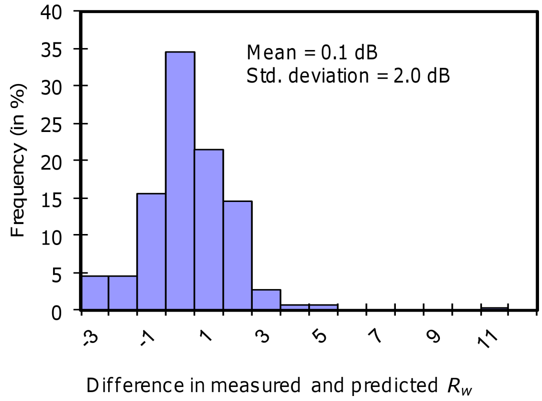

Fig. 8. Histogram showing the frequency (in %) of prediction error, i.e. difference between the measured and predicted R_w for 283 sandwich gypsum constructions.

it can be concluded that the developed ANN model shows a prediction error of ±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 multilayered 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 ±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.

Acknowledgments

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