RECENT DEVELOPMENTS IN THE APPLICATION OF NEURAL NETWORK ANALYSIS TO ARCHITECTURAL AND BUILDING ACOUSTICS

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Abstract: This paper reviews the work undertaken in the Department of Architectural and Design Science University of Sydney, on the use of neural network analysis in architectural and building acoustics. In auditorium acoustics, developments include the use of neural networks to predict acoustical attributes of concert halls: attributes such as reverberation time, RT_{60}, strength factor, G, clarity factor, C80, and lateral fraction, LF. Investigations have also been undertaken relating the acoustic quality of auditoria, as judged by conductors and musicians, to ten hall 'geometric' parameters and six acoustic parameters. In the area of small rooms, investigations have been carried out to predict the acoustic quality of music practice rooms and music teaching rooms by utilizing a combination of geometric variables as inputs. In rooms used for speech, neural network analyses have been undertaken to predict speech levels in university classrooms. Finally, in the area of noise control in buildings, work has been carried out using neural networks to predict the properties of acoustical materials such as sound transmission loss (wall sound insulation) and absorption coefficients. The results of the work undertaken have shown the potential usefulness of neural networks as design tools and, significantly, that neural network techniques have a role to play in the field of architectural and building acoustics.

1. INTRODUCTION

Sabine (1900) laid the groundwork for architectural acoustics and defined the subject in fairly simple terms. Everything that was simple at the end of Sabine's time appeared to become complicated and, by the 1950s, architectural acoustics had been turned into a complex subject. This is understandable as the field is broad and research activities have been carried out over a large range of topics. Unfortunately, the research has been and is often being directed to work which unavoidably conforms to traditional architectural acoustics precepts. Although the research has been of benefit to the acoustic community, architects and acousticians have continued to fail to come to terms with the concept that acoustically good auditoria cannot be directly scaled up or down to achieve good acoustics in new halls in the same manner in which visual aspects can be. A reason for this is the enormous difficulties that are created by the multiple parameters and multiple criteria aspects of architectural acoustics. These complex situations are not easily recognizable and therefore remain difficult to resolve using conventional methods. This paper summarizes research carried out, using a new approach to help architects and acousticians solve complex architectural and building acoustic design problems.

The new approach being researched at the University of Sydney involves the development of neural networks to investigate the many issues and problems that exist in the multi-disciplinary field of architectural and building acoustics and which are not readily handled by conventional methods. Neural network analysis (*NNA*) can be compared to multiple regression analysis except that with *NNA* assumptions need not be made about the system being modelled. Neural networks already perform successfully where other methods do not; they have been applied in solving a wide variety of problems including those in the area of civil and structural engineering where they have been used extensively [1]. The history and theory of neural networks, and some indications of their future utility, have been described in a plethora of published literature, for example [1–4], therefore, only a very brief overview of how neural networks operate will be covered in this paper. Suffice to say that neural networks obviate the need to use complex wave theory, and computer models, and impractical and costly physical models.

The major part of the work covered in this paper relates to investigations undertaken using neural networks in the area of room acoustics. Also presented is research with neural networks in the area of noise control in buildings, i.e. properties of acoustical materials and constructions.

2. NEURAL NETWORK ANALYSIS

There are many alternative forms of neural networking systems and there are many ways neural networks may be applied to a given problem. The suitability of an appropriate paradigm and strategy for application is very much dependent on the type of problem to be solved. The types of networks applied to many of the problems presented in this paper are the basic multilayer feedforward neural networks (see Figure 1). These networks perform a non-linear transformation of the input data in order to approximate output data. The number of cases (input and output parameter sets) influence the architecture of a multilayer feedforward network. The topology of a network consists of an input layer of neurons (one neuron to each input) a hidden layer or layers of neurons (one layer is usually considered sufficient) and an output layer of one neuron for each output. A neuron, also called a processing element (see Figure 2), is the basic unit of a neural network and executes a summation and activation function to determine the output of that neuron. The number of neurons in the hidden layer is approximately the average number of the inputs and outputs, though this number is also influenced by the number of training cases. For instance, too many neurons in the hidden layer can result in over-training (a lack of generalization which can be overcome by a number of strategies [5]) and lead to large verification errors. On the other hand, too few neurons can result in large training and verification errors.

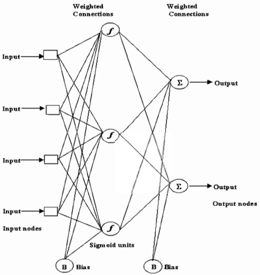

Figure 1: A multilayer feedforward neural network

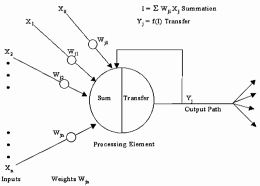

Figure 2: How a processing element (neuron) works. The notation W_{ji} represents the connection weight from the jth neuron to the ith neuron. (after Nelson, and Illingworth [27])

Inputs to a neural network are presented at the input layer. Starting from an initially randomized weighted network system, input data is propagated through the network to provide an estimate of the output value. The error between the actual output and the predicted value is used to adjust the network weightings (on the connections between neurons) to minimize the error in the predicted outputs. In this iterative procedure, the new weights are accepted if the resulting error is smaller than that recorded using the previous set of weights. Several algorithms [2–4] are commonly used to achieve the minimum error in the shortest time.

Some of the characteristics that support the success of neural networks and distinguish them from the conventional computational techniques are:

- The direct manner in which neural networks acquire information and knowledge about a given problem domain [6–17] (learning interesting and possibly non-linear relationships) through the training phase.
- Neural networks can work with numerical or analogue data that would be difficult to deal with by other means because of the form of the data or because there are so many variables.
- Neural network analysis can be conceived of as a black box approach and the user does not require sophisticated mathematical knowledge.
- The compact form in which the acquired information and knowledge is stored within the trained network and the ease in which it can be accessed and used.
- Neural network solutions can be robust even in the presence of noise in the input data.
- The high degree of accuracy reported when neural networks are used to generalize over a set of previously unseen data (not used in the training process) from the problem domain.

While neural networks can be used to solve complex problems, by what can be simply considered an interpolation process involving multivariate nonlinear mappings (in some cases mapping is acquired automatically and very fast because of the inherent parallel nature of NNA), they do however suffer from a number of shortcomings:

- The data used to train neural networks should contain information which, ideally, is spread evenly throughout the entire envelope of the system.
- There is limited theory to assist in the design of neural networks.
- There is no guarantee of finding an acceptable solution to a problem.
- There are limited opportunities to rationalize the solutions provided.

3. NNA AND ROOM ACOUSTICS

Concert halls: acoustical parameters

Concert hall design, is unique in its complexity. This is mainly because concert hall acoustics, in all its diversity, is a multi-criteria and multi-parameter discipline. Sabine's famous work led to the widespread use of reverberation time. For many years this was the only acoustical parameter used in the design of auditoria. However, uncertainties caused by the audience and performer absorption, together with the many anomalies inherent in the classical equation and other related theoretical formulae, are responsible for the often inaccurate prediction of reverberation times. These predictions are often not within the subjective difference limen of 5%, i.e. $\Delta T/T \approx 0.05$. This reason and because simple and accurate rules of thumb suitable for use at the early conceptual design stage led Nannariello and Fricke [6,7] to investigate an alternative method of predicting reverberation time. It was demonstrated that neural networks can better, more readily and accurately predict low frequency-band $RT_{125\text{-}250}$ and mid frequency-band $RT_{500\text{-}1000}$ reverberation times for auditoria.

Neural networks were trained using constructional and acoustical data of auditoria as input variables. Importantly, the input variables associated with the absorption coefficients were replaced by simple rating coefficients in terms of the absorptivity of materials. The result of this work provided evidence that neural networks 1) can be used to make predictions of reverberation times at low and mid frequencies for auditoria, and 2) that these predictions are as good or better than existing methods. Linear regression analysis of measured versus neural network predicted reverberation times, for low and mid frequency bands, produced R^2s of 0.91, and 0.94 respectively. Furthermore, and more importantly, the results showed excellent strength of association and high percentage agreement (10 out of 12 predictions were greater than 90%) between measured and predicted reverberation times. The results were repeatable and within range of the subjective difference limen of 5%.

Nannariello and Fricke [7] drew from the results obtain previously [6] and extended the idea to using neural networks built with a reduced number of input variables (a network 'dimensionality' reduction) to predict $RT_{125\text{-}250}$ and $RT_{500\text{-}1000}$ for auditoria . The concept was further extended to developing some basic relationships and rules of thumb on how simple geometric parameters affect reverberation time. The results of these investigations are presented in Ref. 7.

It has long been realized that there is more to auditorium acoustics than reverberation time. Over the last 30 years or so, a number of objective acoustical parameters (related to the subjective assessment of the acoustical characteristics of auditoria) have emerged to aid the design of auditoria. Consequently a number of methods have been developed [18-21] to predict parameters such as the strength factor G, the clarity factor C_{80}, lateral energy fraction(LF, and interaural cross-correlation coefficient $IACC$, but these methods have their limitations.

Nannariello and Fricke [9] investigated and developed a method of predicting G, C_{80}, LF, and $1\text{-}IACC_{E3}$ values in auditoria using neural networks. As a trial of this concept, and because well-documented measured data from halls is a rarity, Nannariello and Fricke [8] used neural networks trained using ODEON 3.1 numerical predictions. It was important to determine whether the neural networks could acquire the information and knowledge about the given domain (sound level distribution) and make accurate sound level (strength factor, G) predictions. A number of general conclusions came from this work. Firstly, that a neural network could be trained and tested using numerical predictions. Secondly, that these networks, because they use simple inputs, could be used in the early stage of a design. Thirdly, and most interestingly, that at least for reasonably diffuse shoebox shaped rooms, neural networks could make accurate predictions of G values. And finally, that there was a good basis for carrying out further investigations using noisy and poorly distributed measured data to train neural networks to predict G values and possibly values of other acoustical parameters.

The subsequent work of Nannariello and Fricke [9] provided evidence that non-linear models, such as neural networks trained with geometrical and measured acoustical data, could make predictions of the G, C_{80}, and LF values in concert halls. The predictions were as accurate as those calculated using existing models. The study demonstrated that neural networks could be trained with a handful of simple and available input variables such as the volume, maximum length, total floor area, reverberation time and tube ratio (see below). Between five and eight input variables were used to train networks to predict seat-averaged G, C_{80}, and LF. Six input variables were used to train networks to predict position-dependent G values.

It was demonstrated that the exact positions of seats in a hall were not required to accurately predict the average parameters. For the 126 receiver positions, in the 8 auditoria tested, the neural network analysis produced excellent results. Detailed descriptive analysis of the 8 auditoria in the 1000 Hz octave frequency band produced R^2s between predicted and measured data of between 0.29 and 0.93. More importantly, the absolute average errors and root mean square errors were within the subjective difference limen of G, which is approximately equal to $\pm$ 1 dB. Table 1 shows the accuracy of neural network predictions for the seat-averaged parameters G, C_{80}, and LF. The Table shows that, for the auditoria tested, neural network prediction errors for G, C_{80}, and LF were, in most cases, within the subjective limen of $\pm$1 dB, $\pm$0.5 dB, and $\pm$0.05 dB respectively.

Nannariello and Fricke [10] extended the idea of using neural networks to make predictions of auditorium attributes to using neural networks to develop some basic knowledge and rules of thumb on how simple geometric parameters affect the attributes of an auditorium (in this case G). In this work, the use of acoustical parameters, such as reverberation time, as an input variable, was deliberately avoided. The results showed that neural networks trained with 4 simple geometric input variables—the hall volume, V, the maximum length, L_{MX}, maximum width, W_{MX}, the total acoustical floor area, S_T, and the tube ratio [19], $D_{mean}/(W_{mean} \times H_{mean})$,—where D_{mean} is the mean depth of the hall (distance from front of platform to rearmost wall) and W_{mean} and H_{mean} are the mean width and height respectively—gave accurate predictions of G. Table 2 shows the accuracy of the predictions: the high global correlation coefficient (R^2_G = 0.95) and low global errors (RMS_G = 0.37, $StdErr_G$ = 0.39 and $AbAvErr_G$ = 0.30 dB). The prediction errors are well below the subjective difference limen for G. The other attendant benefit was that the neural network models produced relationships which, in most cases, agreed with the published literature [19,22,23]. That is, G is affected by a number of architectural factors, the most important of which are the distance of the listener from the stage, the presence of reflecting surfaces, the acoustical floor area (the area occupied by the audience), and the volume of the auditorium. Significantly, however, the work also showed that determining the cubic volume and number of seats is not sufficient as a 'rule' in modern auditorium design. The optimization of G is dependent on a combination of geometrical factors including the shape of the hall, which is represented by the tube ratio and the maximum dimensions. This is demonstrated in Figure 3. It shows a three-dimensional quadratic smooth response surface plot of G, as a function of the tube ratio, $D_{mean}/W_{mean} \times H_{mean}$, and the volume, V. The response surface plot also shows the non-linearity of the situation i.e. that the preferred value of G is dependent on the tube ratio and the volume.

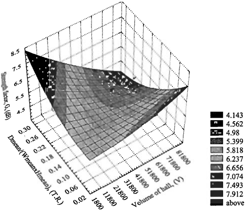

Figure 3: Quadratic smooth surface plot (V, TR, G) showing relationship between averaged acoustic parameter G (dB), hall volume V (m^3) and tube ratio, $D_{mean}/W_{mean} \times H_{mean}$ (m^{-1}) [10].

Continuing with the neural network approach, Nannariello and Fricke [26] investigated a neural-computation method for predicting the early interaural cross-correlation coefficient, $IACC_{E3}$, in unoccupied auditoria. Thirty-six auditoriums were used in the neural network analysis. A multilayer perceptron, fully connected, three layer feedforward network architecture, based on the supervised learning procedure was used to build the neural networks. Seven input variables were used in the first layer. The set-up function for the neural network analyses was: $1\text{-}IACC_{E3} = f(V, L_{MX}, W_{MX}, D_{mean}/W_{mean} \times H_{mean}, S_T, A_w, RT_{mid}$, where the symbols specify quantities previously defined and A_w is the side wall angle of hall, and RT_{mid} is the mid frequency reverberation time. Results of the investigations showed that the neural network model could predict $IACC_{E3}$ values within the subjective difference limen, which is 0.075 ± 0.008. Five auditoria were used to assess the neural network analysis method and the errors between measured and predicted $1\text{-}IACC_{E3}$ ranged from –0.05 to 0.02. The neural network model used to make $1\text{-}IACC_{E3}$ predictions was imbedded in an Excel spreadsheet so that designers and researchers, without assess to specialized neural network software, could use the results of the work.

Concert halls: acoustical quality

Architects and designers, when designing concert halls, still make use of precedents especially at the sketch design stage. This technique, in most cases, has not guaranteed good acoustics. Fricke and Han [13] undertook a neural network analysis which related the acoustic quality of halls, as judged by conductors and musicians (subjective acoustic quality index, *AQI* [12]), to ten hall parameters; volume, surface area, number of seats, length, width, height, rake angle of seats, a surface diffusion index (visually assessed) [12-14], stage height and extent of stage shell/enclosure. Fricke and Han's work demonstrated that neural networks offered the opportunity to study the non-linear interactions of the many variables involved in the acoustic performance of concert halls and evaluate the acoustics of halls though the standard deviation ratio SDR achieved (≈ 0.90) left a lot to be desired. Further, unpublished work has considerably reduced the uncertainty of predictions.

In other work carried out by Fricke [14–15], the visually assessed surface diffusion index SDI, together with Beranek's [23] other orthogonal variables, the early interaural correlation $IACC_{E3}$, the time delay between the direct and first reflected sound at the centre of the main seating area T_I, the early decay time *EDT*, the measure of the average sound level in a hall at mid-frequency G_{mid}, and the bass ratio *BR*, were used as input variables to train neural networks to predict the acoustic quality *AQI*, of halls. The results of the neural network analyses were used firstly to investigate the importance of surface diffusion [14], and secondly they were applied to the Concertgbouw, in Amsterdam, to see how changes in the orthogonal variables might change the acoustic quality *AQI*, of the hall [15].

From the results of the neural network analysis, Fricke [14] concluded that Beranek's approach to the prediction of the acoustic performance of concert halls is valid, however a better way of predicting the acoustic performance may be to use a trained neural network. The neural network results showed that:

- using Beranek's six orthogonal parameters as inputs, better concert halls are achieved with higher *SDI* values
- the importance of *SDI* varies from hall to hall
- in some cases a relatively small error in assessing the *SDI* value could result in a hall being ranked at the opposite end of the quality scale.

Fricke [15] used the Concertgebouw data in a neural network analysis to compare the relatives merits of a number of approaches to predict the *AQI*. Several combinations of Beranek's input variables were used to train a set of neural networks and a second set of neural networks were trained using Beranek's input variables together with the number of seats (N), and the volume of the hall. The results of the neural network analyses were presented as standard deviation ratios, *SDR*s, and as *AQI* response surfaces. The *SDR*s values show the degree to which the data had been fitted. *SDR* value of 0.1 is considered an excellent fit, a ratio of 1 means that the predictions are no better than using the mean value. Response surface plot technique was used to show the relationship between parameters and *AQI*. From the results of neural network analyses using many combinations of input parameters Fricke conclude that:

- Ando's four-parameter model (*IACC*, T_I, G_{mid}, and *EDT*) [25] is not as good as Beranek's model [23] (*SDR*s of 0.87 and 0.40 respectively).
- A five-parameter model using (*IACC*, T_I, G_{mid}, *EDT*, and *SDI*) appears to be only marginally worse than the six-parameter model *SDR*s of 0.42 and 0.40 respectively. A four-parameter model using (*IACC*, *EDT*, G_{mid} and *SDI*) is marginally better for predicting *AQI* (*SDR* =0.37) than Beranek's six parameter model.
- There does not appear to be linear relationship between *AQI* and some of Beranek's parameters.
- A Bass Ratio *BR*, of less than 1.0 is preferred and is contrary to accepted wisdom.
- It is possible to obtain better predictions of the acoustic performance of concert halls using *IACC*, T_I, G_{mid}, *EDT*, *SDI* and *N* or *IACC*, G_{mid}, *EDT*, *BR*, *SDI* and *N* than it is using any combination of Beranek's parameters (*SDR*s of 0.25 and 0.33 respectively).

Rooms for speech

It would be very useful at the schematic design stage of a classroom, to have an expeditious and accurate method of predicting the distribution of sound levels (speech levels). Nannariello, Hodgson and Fricke [11] investigated and developed a method of predicting the Sound Propagation *SP*, in university classrooms. The *SP* is the variation of sound pressure level, normalized to the source power level, with distance from an omnidirectional source. Constructional and acoustical data for 34 randomly chosen unoccupied University of British Columbia (UBC) classrooms were used for the neural network analyses. The results of this work showed that neural networks trained with variables that have a causal relationship to the acoustical quality of the UBC classrooms produce reliable and accurate predictions. *RMS* errors for *SP* in each of the frequency bands, were within the subjective difference limen for steady-state sound pressure levels, which is about 1 dB (i.e. $\Delta E/E = 0.26$ where E is the energy density). Furthermore, results showed that *SP* predictions for classrooms were in better agreement with measured values than those obtained using Barron's revised theory [18] or the Hopkins-Stryker equation.

The good fit between measured and predicted *SP* values for the four classrooms tested was highlighted by the high correlation (R^2 = 0.97). The average error and standard deviation of the variations () between measured and predicted *SP* in the octave bands 125 to 2000 Hz ranged between –0.72 (0.35) and +0.69 (1.05) dB, confirming that in most cases the error was relative small and that predictions of speech levels at listener positions were accurate to within the magnitude of the subjective difference limen. Table 3 highlights, for example, the accuracy of neural network predictions, in the 4 classrooms tested, in the 1000 Hz octave frequency band.

Small music rooms

A large amount of research has been undertaken on acoustics of auditoria for the performance of live music and for speech, but there has been very little research carried out on the acoustics of smaller rooms used as music rooms and music teaching rooms. Osman and Fricke [16] developed a method of predicting the acoustic quality of small music rooms by utilizing a neural network trained with data collected and measured using binaural recordings made in the small music rooms. The 36 rooms used in the investigations were parallelepipedic with volumes ranging from 24 to 427 cubic metres. A combination of simple input variables for four musical instruments (cello, saxophone, trumpet, and guitar) was used to build a number of neural networks. The neural network models were used to predict the *AQI* of six small music rooms. From the results of the investigations Osman and Fricke concluded that neural network models can be used to predict acoustic performance of small music rooms, and that room volume, reverberation time, and room height are the most significant elements that determine *AQI*.

4. NNA AND NOISE CONTROL IN BUILDINGS

Sound transmission loss

Bearing in mind that the method of determining the transmission loss can be both expensive and time consuming Coomes and Fricke [17], using the results from acoustic laboratory tests on known partitions, investigated the application of neural network analysis for predicting the sound transmission class, *STC*, and transmission loss, *TL*, at specific frequencies, for different types of drywall constructions. Basic parameters (stud frame size, mass of wall construction, the inclusion, type and with of any insulation, overall partition width, minimum sheet lining thickness, and the difference in sheet lining from one side to the other), were used as inputs for the neural network analysis. The total number of training cases used in the neural network analyses was 128 (this included walls with isolated or resilient framing systems).

The results obtained were highly encouraging, with neural network designs achieving predictions for *STC* values within a similar range to those determined by a number of acoustic laboratories for comparable wall constructions. For instance, using data from the Canadian NRC on all types of dry wall constructions a neural network was trained to predict *STC* values within a *RMS* error of *STC* 2.01. The training data included partitions with *STC* ratings between 32 and 60. The inputs variables used in this case were type of studs (timber or steel), type of fixing (direct or vibration isolated), mass of wall, overall thickness and absorbent infil type (none, mineral wool, fibreglass, polyester or cellulose). Coomes and Fricke concluded that the modelled neural networks provided a good means of predicting *STC*, and that the significant computational effort required by other simulation methods are considerably improved on by the use of neural networks which provide a less complex prediction technique.

Sound absorption coefficients

Current measurement techniques for absorption coefficients, can give results from different laboratories which are more than 20% different. Such difference can mean the difference between winning and loosing a contract worth million of dollars. As part of the research program at the University of Sydney, attempts were made to develop a method of predicting sound absorption coefficients at specific frequencies, which was more reproducible and less costly and demanding than existing methods, by exploring the possibilities of applying *NNA*. Neural networks were first used to examine the influence of various air gaps on the absorption performance of porous materials. The neural network analysis used 8 input variables, the depth function (the air gap distance), the thickness of the material, and results of absorbent coefficient test at each of the octave frequencies. The analyses used a sample of 14 different ceiling tiles tested over a range of air gaps in order to learn a pattern of influence of air gap distance on the absorption coefficient. The results showed that neural networks were capable of mapping the absorption coefficients. In each of the specific frequency bands the error between known and predicted values of absorption coefficients was 5 to 10%. This work is continuing.

5. CONCLUSIONS

Indications are that concert hall design is ready to develop into a more scientific discipline. While art will always have a role in the design of concert halls, neural-computations present the opportunity of to extend the degree of science in the design process. The results of investigations carried out so often suggest that neural network techniques appear to be particular appropriate for application at the conceptual stage of a design. Neural network analysis approach not only considers the possible non-linearity of the combination of factors pertinent to the acoustic quality of a hall but it makes use of precedents which are intrinsic in the neural network model.

The work presented in this paper as shown that the neural network technique, using limited input variables, has been successfully used to predict the acoustic quality of concert halls and small music rooms. It has also been used to establish and investigate guidelines and rules of thumb for concert hall design. Furthermore, results of work in the area of auditoria for music and auditoria for speech have shown that neural networks—though not without limitations—can be successfully used to make accurate predictions of acoustical parameters, at an early stage of the design.

Testing the acoustic performance of various types of wall constructions and calculating the sound absorption coefficient materials require complex and costly techniques which require excess computer and analysis time. The work presented here has shown that there is potential for the neural networks technique to mitigate some of the costly issues associated with the laboratory testing. In addition, the technique can be used as design tool to complement formal acoustic testing and at the same time provide accurate predictions for *STC* and sound absorption coefficients at specific frequencies.

The most general conclusion to come out all the work undertaken and presented here is that the results of the investigations have shown the potential usefulness of neural networks as design tools. Furthermore and significantly, neural network techniques have a definite role to play in the field of architectural acoustics and in the acoustic community at large. Finally, it is hoped that ongoing research in this field will lead to other applications and the development of more robust [5,24] neural networks to further improve their efficacy in making accurate predictions of acoustical parameters.

Table 1: Descriptive statistics of averaged parameters, *G*, C_{80}, and *LF* predictions for auditoria 'tested' using neural networks (see Ref. 9).

Halls	*G_Meas*	*G_P_NN*	*G_Err*	*C₈₀_Meas*	*C₈₀_P_NN*	*C₈₀_Err*	*LF_Meas*	*LF_P_NN*	*LF_Err*
1	5.58	5.03	-0.55	-1.96	-2.12	-0.17	0.13	0.18	0.04
2	6.54	6.74	0.20	-5.14	-4.13	1.01	0.16	0.18	0.02
3	3.41	3.08	-0.33	-1.51	-1.21	0.30	0.27	0.17	-0.09
4	2.86	3.09	0.22	-1.66	-1.36	0.30	0.16	0.21	0.05
5	1.58	1.30	-0.29	0.67	1.00	0.33	0.18	0.20	0.02
6	5.50	4.56	-0.94	-4.36	-3.81	0.55	0.17	0.18	0.01
7	3.57	3.85	0.28	-2.15	-3.30	-1.15	0.20	0.17	-0.03
8	4.38	5.20	0.81	-	-	-	-	-	-

G_Meas = Measured strength factor, G, (dB)

G_P_NN = Neural network predicted strength factor, G, (dB)

G_Err = Error between measured and predicted strength factor, G, (dB)

C80_Meas = Measured clarity factor, C80, (dB)

C80_P_NN = Neural network predicted clarity factor, C80, (dB)

C80_Err = Error between measured and predicted clarity factor, C80, (dB)

LF_Meas = Measured lateral fraction, LF

LF_P_NN = Neural network predicted lateral fraction, LF

LF_Err = Error between measured and predicted lateral fraction, LF

Table 2: Descriptive statistics of neural network trained with set up function $G = f(V, L_{MX}, Tube\ Ratio, S_T)$ used to predict average G values for the 7 enclosures for which the resulting $R^2G^a = 0.95$, $StdErr_G{}^b = 0.39$, $AbAvErr_G{}^c = 0.30$ and $RMS_G{}^d = 0.37$ (see Ref. 10)

Halls	Measured G values (dB)	Neural network Predicted G values (dB)	Error between measured and predicted values (dB)
1	5.58	4.89	-0.69
2	6.54	6.87	0.33
3	3.41	3.46	0.05
4	2.86	3.38	0.52
5	1.58	1.81	0.23
6	5.50	5.61	0.11
7	3.57	3.43	-0.14

[a] R^2_G = Global correlation coefficient between the measured and predicted G

[b] $StdErr_G$ = Standard deviation of errors between the measured and predicted G for the seven halls (dB)

[c] $AbAvErr_G$ = Absolute average error between the measured and predicted G, for the seven halls (dB)

[d] RMS_G = Root mean square error between the measured and predicted G, for the seven halls (dB)

Table 3. Descriptive statistics of a neural network result for Sound Propagation, SP, predictions for 4 classrooms at a total of 20 listener position in the 1000 Hz octave band. SP = sound pressure level minus sound power level (Lp-Lw) at that position (dB) (see Ref. 11)

Classroom	Ros (m)[a]	M_SP[b]	P_Nnet[c]	R^{2d}	Err_SP[e]	NN_RMS[f]
C3	0.50	-6.16	-4.92		1.24	
	1.00	-9.39	-9.54		-0.15	
	2.00	-15.70	-14.05		1.65	
	5.00	-18.50	-19.19		-0.69	
	10.00	-20.50	-21.50	0.98	-1.00	1.07
C7	0.50	-6.16	-6.25		-0.09	
	1.00	-9.39	-9.53		-0.14	
	2.40	-11.80	-13.12		-1.32	
	5.00	-14.40	-13.63		0.77	
	10.00	-14.90	-14.73		0.17	
	15.00	-16.00	-15.42	0.96	0.58	0.68
C16	0.50	-6.16	-6.18		-0.02	
	1.00	-9.39	-8.84		0.55	
	2.00	-12.10	-11.14		0.96	
	5.00	-13.40	-13.35	0.98	0.05	0.55
C27	0.50	-6.16	-5.95		0.21	
	1.00	-9.39	-10.17		-0.78	
	2.00	-12.60	-13.35		-0.75	
	5.00	-16.60	-16.20		0.40	
	9.00	-19.40	-17.54	0.97	1.86	0.98

[a] R_{OS} = Distance between sound source and listener position (m)

[b] M_SP = Measured Sound Propagation, SP, at listener position (dB)

[c] P_NNet = Neural network predictions of Sound Propagation, *SP* (dB)

[d] R^2 = Coefficient of determination (correlation coefficient)

[e] Err_SP = Error between measured and predicted Sound Propagation, *SP* (dB)

[f] NN_RMS = The root mean square error of measured and predicted Sound Propagation, *SP* (dB)

REFERENCES

1. Nannariello, J., Fricke, F.R., "Introduction of neural network analysis and its application to building services engineering," *Building Services Engineering Research and Technology*, **22**(1), 61–71 (2001)
2. Hertz, J., Krogh, A., and Palmer, R.G., *Introduction to the theory of neural computation*. Addison-Wesley New York (1991).
3. Fausett, L., *Fundamental of Neural Networks*. Prentice Hall, New York (1994).
4. Baillie, D., and Mathew, J., "Diagnosis rolling element bearing faults with artificial neural network," *Acoustics Australia*, **22**(3), 79–84 (1994).
5. Martin, E.B., and Morris, A.J., *Artificial neural Network and Multivariate Statistics. In: Statistics and Neural Networks – Advances at the Interface*, Edited by Kay, J.W., and Titterington, D.M. Oxford University Press (1999).
6. Nannariello, J., and Fricke, F.R., "The prediction of reverberation time using neural network analysis," *Applied Acoustics*, **58**, 305–325 (1999).
7. Nannariello, J., Fricke, F.R., "The prediction of reverberation time using optimal neural networks," *Journal of Building Acoustics* (in press) (2001)

8. Nannariello, J., and Fricke, F.R., "The use of neural network analysis to predict the acoustic performance of large rooms: Part I Predictions of the parameter G utilizing numerical simulations," *Applied Acoustics*, **62**(8), pp.917–950 (2001).
9. Nannariello, J., and Fricke, F.R "The use of neural network analysis to predict the acoustic performance of large rooms: Part II Predictions of the of the acoustical attributes of concert halls utilizing measured data," *Applied Acoustics*, **62**(8), pp.951–977 (2001).
10. Nannariello, J., and Fricke, F.R., "A Neural Network Analysis of the effect of geometric variables on Concert Hall G values," *Applied Acoustics* **62**(12), 1397–1410 (2001).
11. Nannariello, J., Hodgson, M., and Fricke, F.R., "Neural network predictions of speech levels in university classrooms," *Applied Acoustics*, **62**(7), pp.749–767 (2001).
12. Fricke, F.R., and Haan, C.H., "Predicting the Acoustics of Concert Halls Using an Artificial Neural Network," *Acoustics Australia*, **23**(3), 87–95 (1995).
13. Fricke, F.R., and Han, Y.G., "A neural Network Analysis of Concert Hall Acoustics," *Acustica*, **85**, 113–120 (1999).
14. Fricke, F.R., "Visual assessments of the surface diffusion properties of concert halls," *Applied Acoustics*, **60**, 253–261 (2000).
15. Fricke, F.R., "Concert Hall Acoustics: an Alternative Approach," *Journal of Building Acoustics*, **7**(4), 233–246 (2000).
16. Osman, M.R., and Fricke, F.R., "Predicting the acoustical quality of small music rooms," Australian Acoustical Society Conference, Brisbane, Australia, November, 13–15 (1996).
17. Coomes, J., and Fricke, F.R., "The Prediction of Wall Sound Insulation Using Neural Networks," *Journal of Building Acoustics* (in press 2001)
18. Barron M., and Lee, L-J., "Energy Relation in Concert Auditoria. I," *J. Acoust. Soc. Am.*, **84**(2), 618–628 (1998).
19. Gade, A.C., "Prediction of Room Acoustical Parameters," A paper presented on the 121st Meeting of the Acoust. Soc. Am., Baltimore, May 1991 (1991).
20. Bradley, J.S., "Comparison of concert hall measurements of spatial quality," *J Acoust. Soc. Am.*, **96**(6), 3525–3535 (1994).
21. Vorlander, Michael, "International Round Robin on Room Acoustical Computer Simulation," 15th International Congress on Acoustics Trondheim, Norway 26–30 June, 689–692 (1995).
22. Gade, A.C., "Room acoustic properties of concert halls: quantifying the influence of size, shape and absorption area," 3rd ASA/ASJ meeting, Honolulu, paper 5aAA1, 1–6 (1996).
23. Beranek, L.L., *Concert and Opera Halls: How They Sound*, Acoust. Soc. Amer., Woodbury, New York (1996).
24. Tickle, A,B., Andrews, R., Golea, M., and Diederich, J., *Rule extraction from trained artificial neural networks*, In: *Neural Network Analysis, Architecture and Applications*, Ed. Browne, A., Inst. of Physics Publishing, Bristol and Philadelphia (1997).
25. Ando, Y., *Concert Hall Acoustics*, Springer-Verlag, Berlin, (1985).
26. Nannariello, J., and F.R., Fricke, "A neural computation method of predicting the interaural cross-correlation coefficient. IACCE3, for auditoria," *Applied Acoustics*, (in press 2001).
27. Nelson, M.M., and Illingworth, W.T., *A Practical guide to neural nets*. Addison-Wesley, New York, (1991).