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Reverberation times prediction on classroom using neural networks model

Musli Nizam bin Yahya (1,2), Toru Otsuru (1) Reiji Tomiku (1) Takeshi Okuzuno (1) and Toshiki Nagasawa (1)

(1) Department of Architecture and Mechatronics, Faculty of Engineering, Oita University,
700 Dannoharu, Oita 870-1192, Japan
(2) Department of Mechanics, Faculty of Mechanical and Manufacturing Engineering,
Universiti Tun Hussein Onn Malaysia (UTHM), Parit Raja, Batu Pahat,
86400, Johor, Malaysia

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ABSTRACT

The purpose of this study is to develop an Artificial Neural Network (ANN) model for predicting reverberation times in classrooms. In order to develop the model, more than 700 samples of room acoustics simulation based on the finite element method are conducted. The simulation system is developed at Oita University as "Large-scale finite element sound field analysis (LsFE-SFA)" and its accuracy has been confirmed in previous papers. With the LsFE-SFA, the sound fields in one classroom at Oita University are analyzed by changing their absorption conditions. Classroom elements like floor, ceiling, wall, window, furniture and door are taken into account in the analyses, and one-octave-band-pass-filtered impulse responses 500 Hz octave band are simulated at several receiving points in the classrooms. The simulated results are provided as training database into the learning process of ANN. In the process, back propagation with Levenberg-Marquardt training algorithm is employed. To confirm the validity of the trained ANN at actual classroom, three conditions of classroom are created; **A**. original classroom; **B**. tiled carpet attached on the door ; **C**. tiled carpet attached on the window. Then, these conditions are measured using Time-Stretched-Pulse-method to obtain reverberation times. The results are compared with the output of ANN and FEM. Acceptable agreement is found at ANN with $MSE_{mea,ANN} = 2.09 \times 10^{-3}$, while sufficient results is from FEM with $MSE_{mea,FEM}$ is 5.4×10^{-3}. In this study can be said the ANN model able predict reverberation times within 1 s on standard PC and the developed ANN is expected to be useful for practical usages.

INTRODUCTION

Reverberation time (RT) is one of the important acoustic parameters that should be considered in classroom acoustics. It is recommended that the RT in a standard classroom should be less than $1s$ between 500 Hz and 1 kHz. In general three factors affect the RT value; the volume, proportion (shape) and material absorption coefficient.

Practically, measuring method is commonly used to obtain the RT because it offers accurate results. However, it is impossible to measure the room under construction or un-existed (on paper design). To overcome the problem, the classical methods namely Sabine and Eyring equations are used. Even thought the implementation of equation is easy but it is compromised for non-diffuse and non-uniform surface absorption surroundings. Therefore, many researchers propose new methods to surpass those kinds of lacking on the classical methods [1, 2, 3].

This study presents a computer program model with possessing the less time of analysis and friendly user interface. The model called Artificial Neural Network (ANN). The purpose of this study is to develop a model which can predict RT by using ANN. To achieve that, FEM is used to simulate a database and fed into ANN for learning process. The FEM analysis was chosen because of high accuracy especially in the lower frequency regions. The building elements (i.e floor, ceiling, wall, window and door) and furniture (i.e tables and chair) in a classroom are implemented as parameter. While, one-octave-band-pass-filtered impulse response centered at 500 Hz are simulated at several receiving points.

LARGE-SCALE FINITE ELEMENT SOUND FIELD ANALYSIS

The Finite Element Method (FEM) procedure is based on the principle of minimum of total potential energy applied to the three dimension sound field. The discretized matrix equation for the sound field in the frequency domain expressing as follows [4];

$$(\mathbf{K} + i\omega\mathbf{C} - \omega^2\mathbf{M})\mathbf{p} = i\omega\rho v_0\mathbf{W} \quad (1)$$

where **M**, **C** and **K** are acoustic mass, dissipation and stiffness matrices, respectively. Besides that, i, $\mathbf{p}$, ρ, ω, v_0 and **W** are respectively imaginary unit ($i^2 = -1$), sound pressure vector, the air density, angular frequency, the particle velocity and distribution vector. By assuming $\cdot$ and $\cdot\cdot$ are first order and second order derivatives in time, the semi discrete equation in time domain can be evaluated using Eq. 2 as shown below.

$$\mathbf{M}\ddot{\mathbf{p}} + \mathbf{C}\dot{\mathbf{p}} + \mathbf{K}\mathbf{p} = \rho\dot{v_0}\mathbf{W} \quad (2)$$

To calculate Eq. 2, the Newmark scheme [5] is used.

The linear system of equations at each time step is solved by

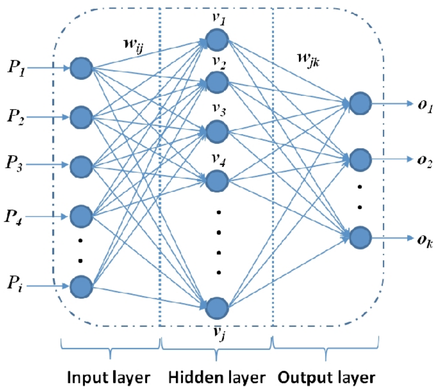

Figure 1: ANN architecture

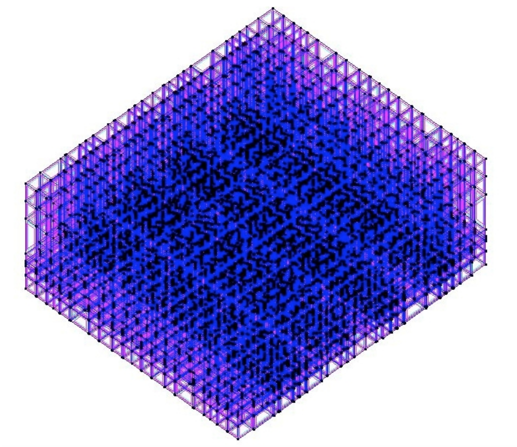

Figure 2: Classroom mesh

absolute diagonal scaled COCG iterative solver. The converge is set to 10^{-6} For spatial discretization, the hexahedral 27 -node isoparametric elemet using the spline function as an interpolation function is adapted [6]. For the details of time domain formulation used here, see the references [7, 8].

ANN ANALYSIS

This study uses Multilayer Perceptron (MLP) using backpropagation algorithm with Leverberg-Marquardt training (*trainlm*). This training method is chosen because it is faster than other methods despite more memory required [9]. Basically, MLP architecture has three layers, which are input layer, hidden layer and output layer as shown in Figure 1. Each layer includes number of neuron to create connections and to make a set of networks. The connections of networks can be interpreted by following equations;

$$v_j = \sum_{i=1}^{m} P_i W_{ij} + \theta_j \tag{3}$$

$$y_j = \varphi(v_j) = \frac{1}{1+exp(-v_j)} \tag{4}$$

$$o_k = \varphi(v_k) = \sum_{i=1}^{m} y_j W_{jk} + \theta_k \tag{5}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \tag{6}$$

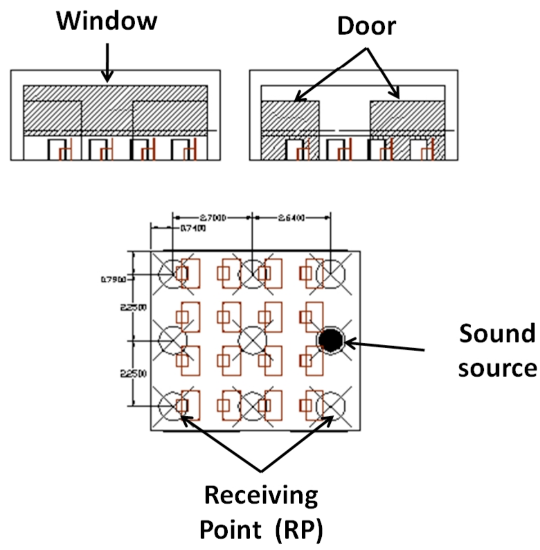

Figure 3: Classroom layout

where MSE is the mean square error, t_i is the desired value (target) and a_i is the output signal (network output), N is the number of samples, v_j is the summation of P_i (input signal), W_{ij} (weight value between input and hidden layer) and θ_j (bias). y_j is the output of hidden layer, $\varphi(v_j)$ is the transfer function (sigmoid function) associated with the neuron j in the hidden layer, o_k is the output of the output layer, $\varphi(v_k)$ is the transfer function of the output layer but in this study used linear transfer function ($\varphi(v_k) = v_k$), w_{jk} is the weight value between hidden and output layer, θ_k is bias at output layer. i , j and k refer to the input neuron $(i = 1,\cdots,m)$ in the input layer, $(j = 1,\cdots,n)$ is the hidden neuron in the hidden layer and $(k = 1,\cdots,q)$ is the output neuron in the output layer, respectively.

To further explain, the ANN learning process begins from Eq. 3, where *trainlm* continuously updates W_{ij} and θ_j. Then, a transfer function, which is also as activation function, modifies v_k using Eq. 4 which is bounded between 0 and 1. Then, y_j is multiply by W_{jk} before adding θ_k to produce the output value (o_k) using Eq. 5. Eq. 6 is used to show that the learning will stops when the error converged to a minimum. In addition, the cross-validation method is used to prevent the phenomena of over-training.

METHODOLOGY: DATA AND PROCEDURE

Source of data

A classroom in Oita University is used as the model where room volume is 130.21 m^3 (7.08 m, 6.09 m, 3.02 m). Here, floor, ceiling, wall, window, door and furniture surfaces consider as the factors to be utilized. Figure 2 shows the mesh of the classroom included the furniture. The mesh can be obtained by using the rule; $\lambda/d > 4.8$ (λ is acoustic wavelength, d is nodal distance)[10]. Then, Gid9 [11] computes the mesh to obtain the numbers of elements and nodes where are used in FEM analysis as shown in Table 1.

Table 1: FEM's setting

No. of	ovr	flr	clg	w	wdw	f	dr
element	60499	3078	2986	459	504	5752	3477
node	515717	3190	3228	520	570	594	3786

ovr = overall; flr = floor; clg = ceiling; w= wall; wdw = window; f = furniture; dr = door

In the FEM, the classroom surfaces of absorption coefficients are employed to simulate the RT. The ranging of the absorption coefficients of the surfaces used are floor: 0.2 - 0.01, ceiling: 0.05 - 0.88, wall: 0.02 - 0.06, window: 0.03 - 0.55, and door: 0 - 0.3. Figure 3 shows that the range for locations is is; x axis: 0.74 - 6.08 and y axis: 0.79 - 5.29. The following equation is expected to generate the RTs from the sample combination coefficient and receiving point locations. It is more than 700 sample have been created.

$$RT = f_{FEM}[\alpha_{flr}, \alpha_{clg}, \alpha_w, \alpha_{wdw}, \alpha_f, \alpha_{dr}, rp_x, rp_y] \quad (7)$$

where f_{FEM} is a function of FEM. The α_{flr}, α_{clg}, α_w, α_{wdw}, α_f, and α_{dr} is represented absorption coefficient of floor, absorption coefficient of ceiling, absorption coefficient of wall, absorption coefficient of window, absorption coefficient of furniture, and absorption coefficient of door, respectively. The rp_x and rp_y are the location of receiving point at x axis and y axis.

ANN Implementation

Eight parameters are to be taken as a set of input parameter; α_{flr}, α_{clg}, α_w, α_{wdw}, α_f, α_{dr}, rp_x and rp_y. The combination of ANN can be simplified as follows;

$$RT = f_{ANN}[\alpha_{flr}, \alpha_{clg}, \alpha_w, \alpha_{wdw}, \alpha_f, \alpha_{dr}, rp_x, rp_y] \quad (8)$$

where f_{ANN} is a function of ANN.

Basically, before executing the training process, a set of data are needed to normalize the parameters between 0.1- 0.9. The normalization can be expressed using the equation as follows;

$$x_{new} = 0.1 + \left[0.8 \times \left(\frac{x_{old} - x_{min}}{x_{max} - x_{min}}\right)\right] \quad (9)$$

where x_{old} is the old value, x_{new} is the new value, x_{min} and x_{max} are the minimum and maximum of the data set. Since the minimum-maximum normalization is a linear transformation, it can preserve all relationship of the dataset exactly.

More than 700 samples are used and they are divided into three subsets; train (60% of samples), validate (20% of samples) and test (20% of samples). The train subset usually used for computing and updating the weights and bias, the validate subset uses to monitor the training process and test subset uses to verify the performance. In addition, 35 unseen data are implemented to confirm the credibility of ANN performance.

Three layers are used to build a network. In input layer, its content eight neurons which represent input parameters. Whereas, only one output neuron states for RT in the output layer. Then the number of neurons in the hidden layer can be added from 2 to 20 neurons to get the optimum network architecture. The networks of ANN should be [i, h,o] for input, hidden and output neuron (i.e [8, 6, 1], [8, 10, 1], [8, 9, 1] or [8, ..., 1]) but only one network may offer a good result. Thus, trial and error is a normal method used to identify the optimum hidden neuron which gives influence to the performance. In this case mean square error (MSE) and correlation coefficients (R^2) are used for the assessment.

RESULTS AND DISCUSSIONS

The optimum network of ANN obtained from 10 hidden neurons (network architecture: [8, 10, 1]). In Table 2, the ANN provides a good performance especially at test subset. The R^2 indicates 98.5% with MSE is 8.318×10^{-4} which means the predicted values are close to actual values.

Table 2: Assessments

type of subset	MSE	R^2
train	3.528×10^{-4}	0.994
validate	8.181×10^{-4}	0.985
test	8.381×10^{-4}	0.985

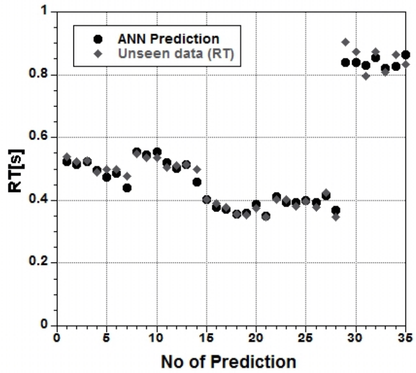

Figure 4: Unseen data prediction

The unseen data are used to verify the performance. The example of unseen data are showed in Table 3. By using the combination of input parameter of unseen data, the ANN are predicted the RTs. Figure 4 illustrates the comparison of ANN prediction between unseen data of RT. The ANN are predicted close to RTs unseen data with the MSE is 4.15×10^{-4}. It is indicated that the ANN give a good agreement in respect to unseen data of RT.

Reliability of Network

To investigate the reliability of the ANN, three conditions of classrooms are created. These conditions and the detail of classroom can be simplified as follows.

- classroom **A**: The original condition of the classroom
- classroom **B**: Tiled carpets are added and attached on door in the original classroom
- classroom **C**: Tiled carpets are added and attached on windows in the original classroom

The absorption coefficients of building elements and furniture are listed in Table 4. Figure 8 illustrates the plan view of furniture layout, location of receiving points and location of sound source in the classroom.

The parameters given in Table 4 are fed into ANN to predict the RTs at each receiving points. Subsequently, a series of measurement is conducted in three conditions of classroom to obtain the RTs following ISO 3382. Figures 5, 6, 7 show the measurement conditions in the classroom. In addition, simulated results of FEM are also provided to compare with those results by ANN and measurement.

Figure 9 presents the comparisons of RT at each receiving points between predicted results by ANN, simulated results by FEM and measured results. Here, the $MSE_{mea,ANN}$ between measured data and ANN is 2.09×10^{-3}, while $MSE_{mea,FEM}$ is 5.4×10^{-3}. It is indicated the predicted ANN is approximated to measured data rather that FEM. This is because of the consistence of ANN prediction located closer to measured data, whereas the FEM is unstable especially at condition **B** and **C** in RP2 and RP3.

Table 3: Unseen data

No. of combinations	α_{flr}	α_{clg}	α_w	α_{wdw}	αf	α_{dr}	rpx	rpy	RT_{unseen}
1	0.2	0.7	0.02	0.18	0.3	0.06	0.74	0.79	0.538
2	0.2	0.7	0.02	0.18	0.3	0.06	0.74	3.04	0.523
3	0.2	0.7	0.02	0.18	0.3	0.06	0.74	5.29	0.525
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	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.
35	0.11	0.42	0.02	0.13	0.02	0.03	6.08	5.29	0.833

Table 4: Classroom condition setting

Condition	α flr	α clg	α w	α wdw	α t	α dr
A	0.022	0.38535	0.0336	0.0731	0.1761	0.13
B	0.022	0.38535	0.0336	0.0731	0.1761	0.062*
C	0.022	0.38535	0.062**	0.0731	0.1761	0.13

* tiled carpet attached on door
** tiled carpet attached on window

Figure 5: Standard classroom

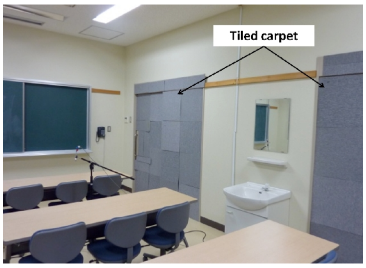

Figure 6: Tiled carpet on door

Figure 7: Tiled carpet on window

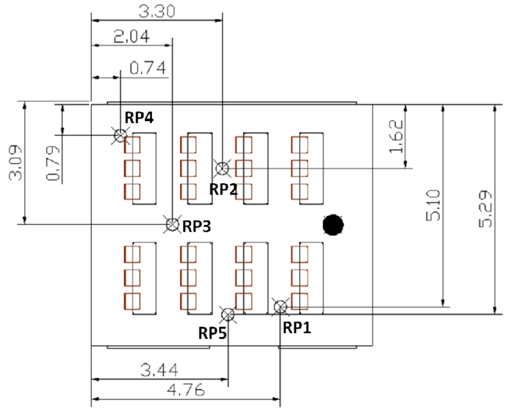

Figure 8: Location of receiving point

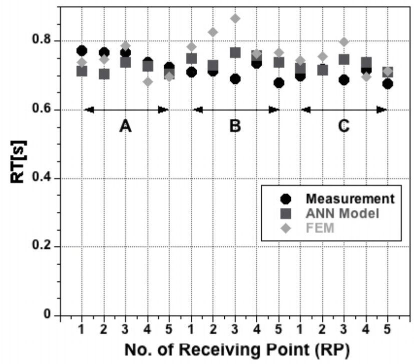

Figure 9: Comparison of ANN, FEM and measurement

In general, the FEM computing time is around few hours. Therefore, this study develops ANN model as a option in predicting the RTs with 1 s. The model is friendly user and can be used in preliminary stage either constructing or renovating classroom with acceptable RTs prediction provided.

CONCLUSIONS

A development of prediction model on RT using ANN in classroom is presented. The capability on ANN predicted in variety of absorption coefficient showed a good agreement with measured data. By using the classroom conditions setting (Condition **A**, **B** and **C**), the comparison between measurement and the ANN gaves acceptable results with the $MSE_{mea,ANN}$ is 2.09×10^{-3} and the analysis only with 1s. Further investigation is required to increase output parameters such as speech intelligibility (D_{50}).

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