

Feed forward neural network application for classroom reverberation time estimation

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ABSTRACT

Acoustic problem is a main issues of the existing classroom due to lack of absorption of surface material. Thus, a feed forward neural network system (FFNN) for classroom Reverberation Time (RT) estimation computation was built. This system was developed to assist the acoustic engineer and consultant to treat and reduce this matter. Data was collected and computed using ODEON12.10 ray tracing method, resulting in a total of 600 rectangular shaped classroom models that were modeled with various length, width, height, as well as different surface material types. The system is able to estimate RT for 500Hz, 1000Hz, and 2000Hz. Using the collected data, FFNN for each frequency were trained and simulated separately (as absorption coefficients are frequency dependent) in order to find the optimum solution. The final system was validated and compared with the actual measurement value from 15 different classrooms in Universiti Tun Hussein Onn Malaysia (UTHM). The developed system show positive results with average validation accuracy of 94.35%, 95.91%, and 96.42% for 500Hz, 1000Hz, and 2000Hz respectively.

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1. INTRODUCTION

Most of the existing classroom are designed for lecture-based education, meanwhile, the growth in education world toward Education 4.0, required the used of education tool and platform to become interactive. This finishes of existing classroom are fine for lecture-based education that may cause acoustic problem in the interactive education, and lead difficult to hear. Reverberation is one of the reasons of the acoustic problem which able to be treatable with the proper mix of absorption. While, surface material; ceilings, concrete walls, wooden walls, tile floors, and wooden doors, plays a critical role of lack of absorption that can creates an excessively reverberant room.

The proposed system of Reverberation Time (RT) computation is able to assist the acoustic engineer and consultant to treat and properly locate the exact specifications of absorption material in order to reduce the classroom acoustic problem. RT is a time taken for the audio signal to drop by 60 dB. The first established formulae in estimating RT in an enclosed space was made by Sabine [1], as seen in (1).

$$RT_{60} = \frac{0.05V}{(\sum s\alpha)} \quad (1)$$

With,

V = room volume

S = surface area

α = material absorption coefficient

Considering the simplicity of the Sabine formulae on top of ignoring many other factors, a jarring error can be seen between the formulaic and the actual measurement RT value. Since then, many other researchers have made improvements and materialized with more solid and accurate formulae calculations in regard of RT [2-6]. Besides this fundamental calculations, other techniques and methods were also being presented such as the computer simulations ray-tracing techniques (ODEON) [7] and finite element models (FEM) [8-9]. As ODEON and FEM taking an extra time on preparations (designing room models, etc.) researchers are still seeking for other alternative methods in estimating RT for instance by using neural network (NN) [10].

Since 1999, researches on RT prediction using NN, were started by Nannarielo and Fricke [11], in order to examine the developed NN using dataset from actual large halls building. This group of researchers were successfully manage and prove that NN is useful in predicting room RT. In 2010, experiments to predict RT for classrooms using dataset gathered from FEM computation were reported by [12]. Research in predicting RT was continued by Aliabadi et al. in 2014 [13]. In this research they were able to strengthen the potential of NN method in minimizing the uncertainties in acoustics' modeling for industrial workrooms.

The purpose of this research is to design an alternate method in estimating RT in a classroom that is cost effective and uncomplicated in addition to be able to provide users with an alternative prediction model with low percentage error. This research focuses on classroom RT computation in order to obtain the optimum sound between the teacher and students, by minimize the noise [14]. Moreover, poor working conditions in a classroom can be avoided as well as maintaining the teacher's comfort in delivering the speech [15]. The ideal classroom RT value is in the range of 0.4 – 0.6 seconds, although most of the existing classrooms produced RT more than 1 second that can cause sounds confusion between teacher's voice and it's reflecting sounds [16]. Therefore, RT has become an important parameter in classroom architectural design in order to achieve and maintain the ideal RT value. Process flow of the proposed system was summarize as in Figure 1.

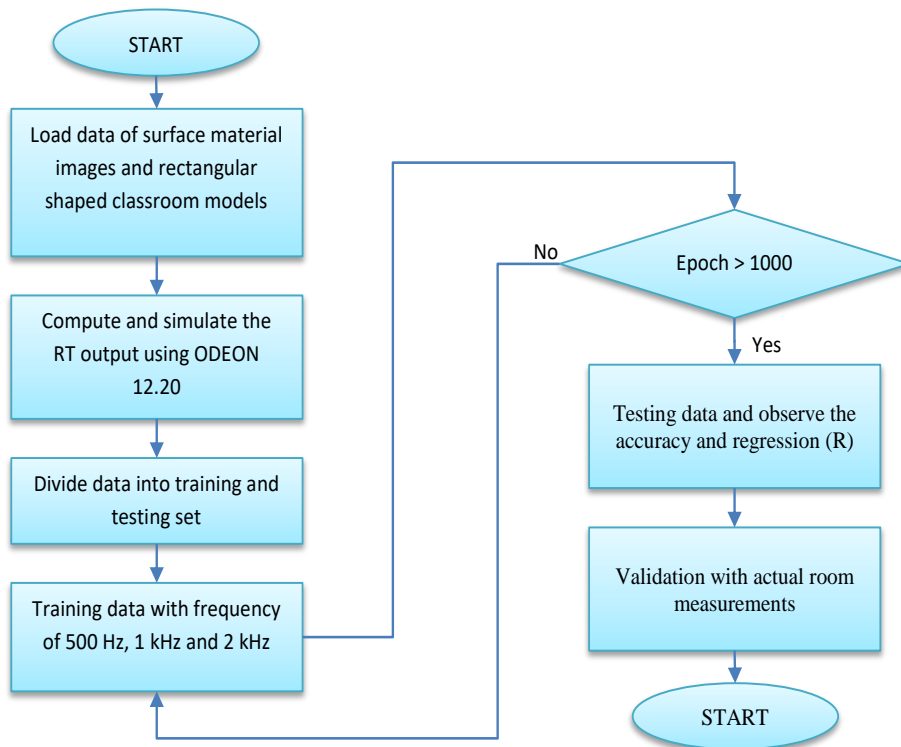


Figure 1. Experimental process flow

2. DEVELOPMENT OF FEED FORWARD NEURAL NETWORK (FFNN) RT PREDICTION SYSTEM

The neural network dataset was collected from rectangular shaped classroom models as seen in Figure 2. This classroom model was sketched using Google SketchUp with different in heights, widths, and lengths. Window was also added to some of the models.

The RT output values from these classroom models were computed and simulated using ODEON 12.10 ray-tracing simulation. Different materials were applied to the surface and the sound source was placed randomly for each model in the dataset. At the end, 600 data that consists of various models and surface materials were successfully gathered.

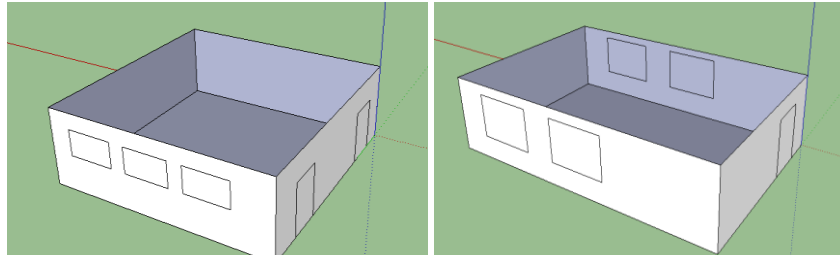


Figure 2. Samples of room models

Frequency of 500Hz, 1000Hz and 2000Hz, were chosen in order to complete the train and analysis of FFNN system. (2), (3), and (4) show RT for 500 Hz, 1000 Hz and 2000Hz, respectively. 13 variables were applied as FFNN input features and requested to compute the RT. Input dataset geometrical characteristics for the FFNN training dataset was shown in [17].

$$RT500 = f(V, L, W, H, Saw1[500], Saw2[500], Saffl[500], Sadoor[500], Sacei[500], Sawin[500], x/L, y/W, z/H) \quad (2)$$

$$RT1000 = f(V, L, W, H, Saw1[1000], Saw2[1000], Saffl[1000], Sadoor[1000], Sacei[1000], Sawin[1000], x/L, y/W, z/H) \quad (3)$$

$$RT2000 = f(V, L, W, H, Saw1[2000], Saw2[2000], Saffl[2000], Sadoor[2000], Sacei[2000], Sawin[2000], x/L, y/W, z/H) \quad (4)$$

3. FEED FORWARD NEURAL NETWORK (FFNN) TRAINING PERFORMANCE

In this experiment, 60%, 20%, and 20% data from the dataset is used as the training data, validation data and testing data, respectively. The training data is used to train and fit the models; the validation data is used to estimate the prediction error for the model selection, as well as prevent network from overfitting; the test set is used for the assessment of the generalization error of the final chosen model [18]. The test data should be unknown or new to the FFNN system. Figure 3 shows the regression plots for training, validation, and testing data for 500Hz, 1000Hz and 2000Hz, respectively.

The optimum network for 500Hz, 1000Hz, and 2000Hz were lastly combined into one final system using Matlab GUI. Figure 4 shows the main page in the final system, where the users are required to fill up the values needed in the NN computation.

Figure 5 shows the interfacing page of adding the material surface. The users have to insert the photographic surface image or select surface images from library as well as its dimension. Figure 6 shows the result page where the RT for 500Hz, 1000Hz, 2000Hz are displayed.

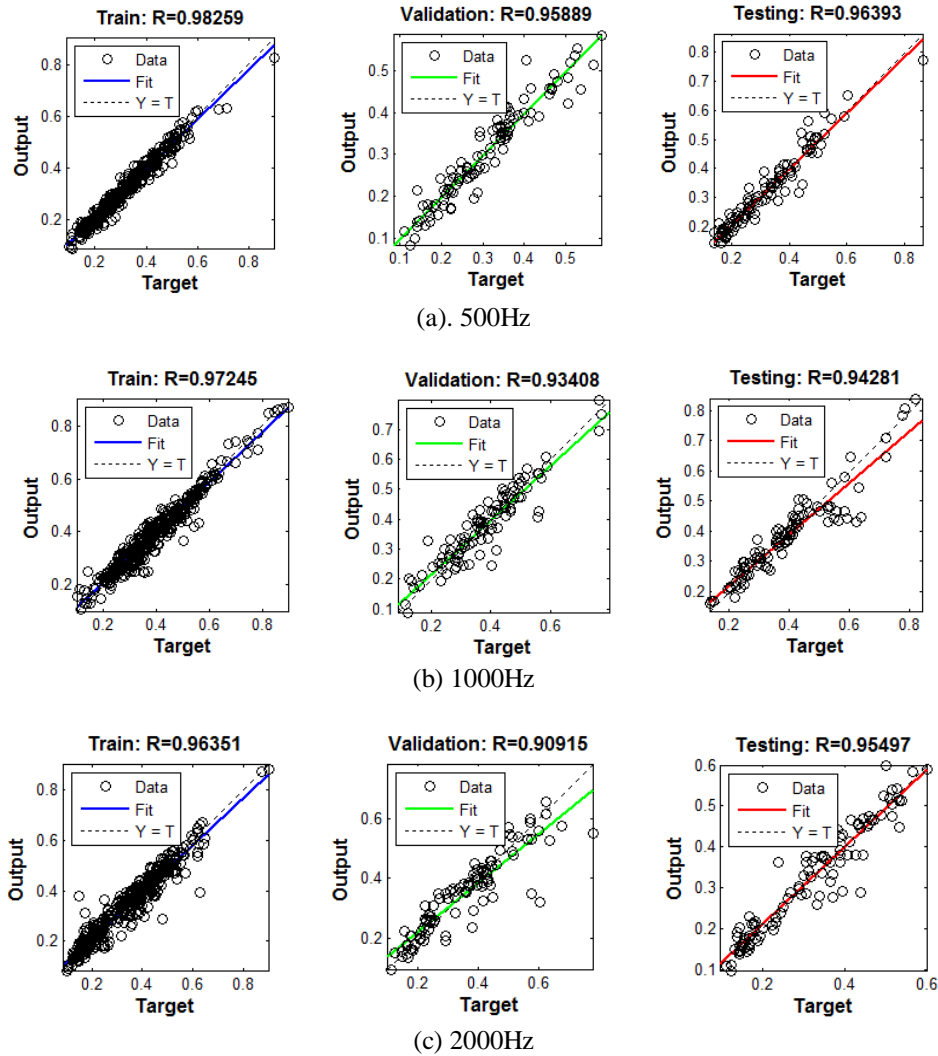


Figure 3. Regression value for (a). 500Hz, (b)1000Hz, and (c)2000Hz

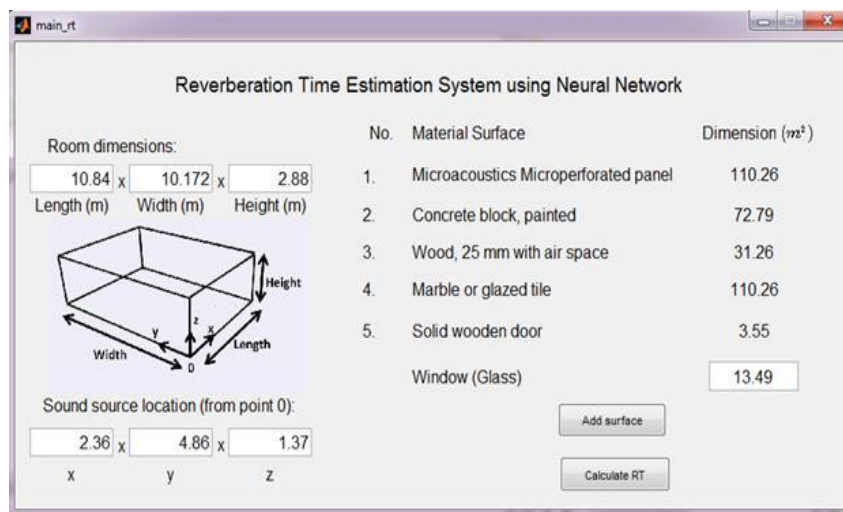


Figure 4. Main page of the system

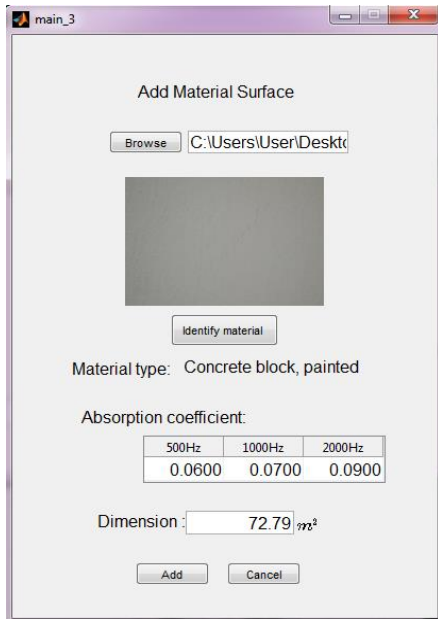


Figure 5. Interface page of adding

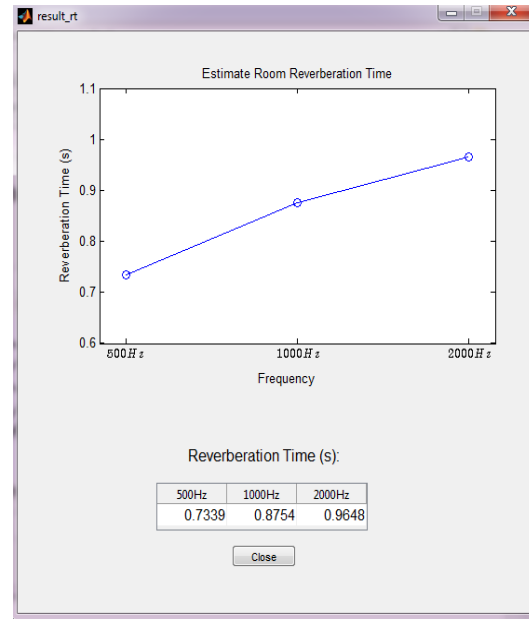


Figure 6. Result page of the system material surface

4. VALIDATION WITH ACTUAL ROOM MEASUREMENTS

The finished system is then applied to the actual classrooms. 15 classrooms (CR01 - CR15) in UTHM were sampled and real-time RT measurements were taken using the regular reverberation room method. Figure 7 shows an example of the actual RT measurement. For comparison, the sampled classrooms were also modeled and simulate using ODEON 12.10 as shown in Figure 8. The geometrical characteristic for these 15 classrooms are compiled in Table 1.



Figure 7. Example of actual room measurement using reverberation time method

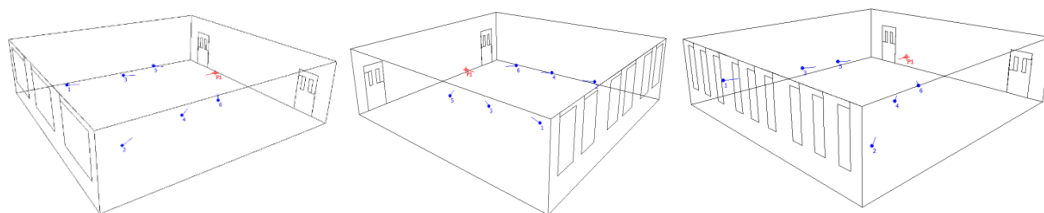


Figure 8. Samples of modeled actual classrooms using ODEON 12.10

Table 1. Room Geometrical Characteristics for NN Validation Dataset

	Max	Min	Mean	Standard Deviation
$V (m^3)$	325.32	300.41	319.899	6.16
$H (m)$	2.88	2.82	2.86	0.025
$L (m)$	10.89	10.20	10.84	0.162
$W (m)$	10.44	10.07	10.35	0.102
$S\alpha_{w1[500]}$	4.68	2.53	4.37	0.94
$S\alpha_{w2[500]}$	5.63	2.76	2.82	1.37
$S\alpha_{fl[500]}$	1.14	1.07	1.12	0.02
$S\alpha_{door[1000]}$	0.21	0.21	0.21	0.00
$S\alpha_{cei[1000]}$	112.41	94.27	110.57	5.66
$S\alpha_{win[1000]}$	2.43	1.42	1.94	0.39
$S\alpha_{w1[1000]}$	5.47	2.96	5.10	1.10
$S\alpha_{w2[1000]}$	3.75	1.84	1.88	0.91
$S\alpha_{fl[1000]}$	1.14	1.07	1.12	0.02
$S\alpha_{door[1000]}$	0.28	0.28	0.28	0.00
$S\alpha_{cei[1000]}$	93.11	72.09	91.73	6.67
$S\alpha_{win[1000]}$	1.62	0.95	1.29	0.26
$S\alpha_{w1[2000]}$	7.03	3.80	6.55	1.41
$S\alpha_{w2[2000]}$	3.75	1.84	1.88	0.91
$S\alpha_{fl[2000]}$	2.27	2.13	2.24	0.03
$S\alpha_{door[2000]}$	0.36	0.36	0.36	0.00
$S\alpha_{cei[2000]}$	86.30	77.64	85.01	2.69
$S\alpha_{win[2000]}$	0.94	0.55	0.76	0.15
x/L	0.515	0.178	0.218	0.079
y/W	0.513	0.415	0.478	0.024
z/H	0.555	0.408	0.454	0.036

^a V , room volume; L , length; W , width; H , height; $S\alpha_{w1}$, equivalent absorption coefficient of wall1 area; $S\alpha_{w2}$, equivalent absorption coefficient of wall2 area; $S\alpha_{fl}$, equivalent absorption coefficient of floor area; $S\alpha_{door}$, equivalent absorption coefficient of door area; $S\alpha_{cei}$, equivalent absorption coefficient of ceiling area; $S\alpha_{win}$, equivalent absorption coefficient of window area; and x/L , y/W , z/H are the sound source position.

Table 2-4 show the results comparison between the actual physical measurement, ODEON 12.10 simulation, and the proposed FFNN system for frequencies of 500Hz, 1000Hz and 2000Hz, respectively. As the initial FFNN trainings were done per frequency, the validation tables were separated in order to observe each FFNN system efficiency.

From the results obtained, it can be observed that the error between the proposed FFNN system and the actual physical measurement are all within the accepted range of $\pm 0.1s$ with the average accuracy percentage of 94.35%, 95.91%, and 96.42% for 500Hz, 1000Hz, and 2000Hz, respectively. The average percentage accuracy between the proposed system and the actual physical measurement is 1.18% lower for the 500Hz frequency, 2.2% higher for the 1000Hz frequency, and 1.1% higher for the 2000Hz frequency than the percentage accuracy between the ODEON simulation and the actual physical measurement. This shows that the proposed system managed to produces up to par results as the ODEON ray-tracing simulation for classroom RT estimation.

Table 2. Validation for 500Hz Frequency

Class room	Actual measurement (s)	ODEON (s)	Proposed Neural network (s)	% accuracy ODEON vs measurement	% accuracy proposed vs measurement
CR01	0.74	0.71	0.73	95.95	98.65
CR02	0.75	0.76	0.79	98.67	94.67
CR03	0.74	0.81	0.79	90.54	93.24
CR04	0.72	0.77	0.80	93.06	88.89
CR05	0.77	0.71	0.81	92.21	94.81
CR06	0.72	0.72	0.81	100.00	87.50
CR07	0.80	0.74	0.81	92.50	98.75
CR08	0.81	0.76	0.78	93.83	96.30
CR09	0.83	0.75	0.78	90.36	93.98
CR10	0.80	0.78	0.79	97.50	98.75
CR11	0.73	0.72	0.78	98.63	93.15
CR12	0.74	0.72	0.81	97.30	90.54
CR13	0.80	0.79	0.85	98.75	93.75
CR14	0.81	0.78	0.83	96.30	97.53
CR15	0.76	0.74	0.80	97.37	94.74
			Average	95.53	94.35

Table 3. Validation for 1000Hz Frequency

Class room	Actual measurement (s)	ODEON (s)	Proposed Neural network (s)	% accuracy ODEON vs measurement	% accuracy proposed vs measurement
CR01	0.85	0.88	0.88	96.47	96.47
CR02	0.85	0.92	0.88	91.76	96.47
CR03	0.87	0.97	0.87	88.51	100.00
CR04	0.86	0.95	0.88	89.53	97.67
CR05	0.85	0.89	0.90	95.29	94.12
CR06	0.81	0.90	0.90	88.89	88.89
CR07	0.87	0.85	0.89	97.70	97.70
CR08	0.90	0.94	0.87	95.56	96.67
CR09	0.89	0.85	0.88	95.51	98.88
CR10	0.88	0.83	0.87	94.32	98.86
CR11	0.95	0.89	0.87	93.68	91.58
CR12	0.82	0.88	0.88	92.68	92.68
CR13	0.92	0.99	0.96	92.39	95.65
CR14	0.92	0.97	0.94	94.57	97.83
CR15	0.84	0.83	0.88	98.81	95.24
			Average	93.71	95.91

Table 4. Validation for 2000Hz Frequency

Class room	Actual measurement (s)	ODEON (s)	Proposed Neural network (s)	% accuracy ODEON vs measurement	% accuracy proposed vs measurement
CR01	0.91	0.89	0.96	97.80	94.51
CR02	0.88	0.93	0.90	94.32	97.73
CR03	0.92	0.97	0.89	94.57	96.74
CR04	0.89	0.94	0.87	94.38	97.75
CR05	0.85	0.90	0.89	94.12	95.29
CR06	0.84	0.89	0.89	94.05	94.05
CR07	0.93	0.85	0.88	91.40	94.62
CR08	0.89	0.87	0.88	97.75	98.88
CR09	0.93	0.88	0.89	94.62	95.70
CR10	0.93	0.83	0.87	89.25	93.55
CR11	0.91	0.91	0.91	100.00	100.00
CR12	0.84	0.88	0.88	95.24	95.24
CR13	0.92	0.91	0.91	98.91	98.91
CR14	0.93	0.89	0.89	95.70	95.70
CR15	0.86	0.84	0.88	97.67	97.67
			Average	95.32	96.42

5. CONCLUSION

An RT estimation system was built using feed forward neural network and the data for the FFNN training was computed using ODEON 12.10 ray-tracing method. The built system shows positive results with average validation accuracy of 94.35%, 95.91%, and 96.42% for 500Hz, 1000Hz, and 2000Hz respectively compared to the actual measurement using reverberation room method. From the results gathered, the built system has shown a huge potential for commercialization although the system works are still wide open for exploration and improvement, such as applying the adaptive filter to eliminate the source of speaker identification noise [19].

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