

RT₆₀ ESTIMATION USING THE SABINE FORMULA AND ANN: A COMPARATIVE STUDY

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Abstract

This paper presents a comparative analysis of reverberation time (RT₆₀) estimation using the Sabine formula and an artificial neural network (ANN) of the MLP (Multi - Layer Perceptron) type. The first part of the study describes the experimental procedure, which includes the generation and processing of room impulse responses (RIRs), the estimation of RT₆₀ using Schroeder's algorithm and the Sabine formula, as well as the training and testing of the ANN. The second part presents a comparison of the RT₆₀ values obtained using the Sabine formula and the ANN with respect to the reference values derived from Schroeder's algorithm, where the results were validated by analyzing the mean square estimation errors (MSE). The experimental results were presented both graphically and numerically using the MATLAB software package.

Keywords: Room Impulse Responses (RIRs), Sabine Formula, Schroeder Algorithm, Artificial Neural Network (ANN), Estimation.

INTRODUCTION

Today, more than a century after Sabine's first experiments, the accuracy of reverberation time (RT₆₀) prediction still represents one of the key challenges in acoustic modeling. Although the physical principles are well established, the behavior of sound energy in complex rooms continues to attract the attention of many researchers due to discrepancies between theoretical, numerical, and experimental results.

At the beginning of the 20th century, Wallace Clement Sabine established the foundation for the quantitative understanding of room acoustics by introducing a formula that relates the room volume and its absorption characteristics to the time required for the sound energy level

to decay by 60 dB after the source has stopped [1]. His simple relation became fundamental in acoustic practice and was later verified through the international standard ISO 3382-1 [2]. However, the accuracy of the Sabine equation decreases significantly in rooms with non-uniform distribution of absorbing materials, complex geometry, or strong frequency dependence of absorption coefficients.

The development of numerical simulations, particularly the Image Method (IM), has enabled the generation and calculation of room impulse responses (RIRs) with high accuracy [3]. At the same time, modern approaches based on artificial neural networks (ANN) have made it possible to predict RT₆₀ without an explicit physical model, representing a significant

advancement in the modeling of acoustic phenomena [4,5].

In this study, a comparative analysis of reverberation time RT_{60} estimation was conducted using the Schroeder algorithm (Sch_alg) [6], the Sabine formula (Sab_form), and a multilayer perceptron (MLP)-based artificial neural network (ANN) [4]. The Sch_alg was used as the reference, while the results of Sab_form and ANN were analyzed in terms of estimation errors (e) with respect to the reference values. The comparison of the obtained results, the errors e , and their mean square estimation errors values (MSE) was carried out in the MATLAB environment, and the results were presented both graphically and numerically.

The structure of the paper is as follows: the first part presents the experimental procedure, which includes the generation of rooms and room impulse responses (RIRs), as well as the estimation of RT_{60} using Sch_alg, Sab_form, and testing of the ANN. The second part presents the results of the comparative analysis and the discussion of estimation errors obtained from the applied estimation approaches, while the third part contains the conclusions of the study.

THE EXPERIMENT

For the purpose of this experiment, RIRs were generated using the IM program described in [3] for a set of 35288 room configurations obtained by combining room dimensions and reflection coefficients within the defined ranges. The program was implemented in the C programming language. The maximum room volume was 500 m^3 .

RT_{60} estimation was performed using: a) the Schroeder integral curve, which was taken as the reference [6]. b) the classical Sabine formula [1], and c) an ANN of the MLP type [4].

For the development of the ANN architecture (13-10-5-1), the dataset was randomly shuffled and divided into two

parts: 70 % (25401 samples) were used for the learning phase, and 30 % (10887 samples) for the testing phase.

Based on the comparison of the estimation errors e_{RT60} and the mean square estimation errors MSE , conclusions were drawn regarding the performance of the applied estimation approaches.

The algorithm according to which the experiment was implemented consists of the following steps:

Input: $W_{min}, \Delta W, W_{max}, H_{max}, R_{min}, \Delta R, R_{max}$.

Output: MSE_{Sch}, MSE_{ANN} .

FOR $x_w = W_{min} : \Delta W : W_{max}$

FOR $y_w = W_{min} : \Delta W : W_{max}$

FOR $z_w = W_{min} : \Delta W : H_{max}$

FOR $R_{l,r} = R_{min} : \Delta R : R_{max}$

FOR $R_{f,b} = R_{min} : \Delta R : R_{max}$

FOR $R_{f,c} = R_{min} : \Delta R : R_{max}$

Step 1: Room dimensions

 ROOM = [$x_w \ y_w \ z_w$]

Step 2: Determination of reflection coefficients

$R = [R_{l,r} \ R_{f,b} \ R_{f,c} \ R_{l,r} \ R_{f,b} \ R_{f,c}]$

Step 3: Calculation of absorption coefficients

$\alpha = 1 - |R|^2$ (1)

Step 4: Position of the loudspeaker (LS)

 LS = [$x_w/2 \ 1 \ 1.5$] (m)

Step 5: Position of the microphone (Mic)

 Mic = [$x_w/2 \ y_w -1 \ 1.5$] (m)

Step 6: Generation of RIR [3]

$h = \text{RIR}(\text{ROOM}, \text{LS}, \text{Mic}, R, c, T_h, f_s)$

Step 7: Estimation of RT_{60} using Sch_alg [6]

$$RT_{60,Sch} = RT_{60,Sch}(h, f_s) \quad (2)$$

Step 8: Estimation of RT_{60} using Sab_form [1]

$$RT_{60,Sab} = \frac{0.161 \cdot V}{A}, \quad (3)$$

where $V = x_w \cdot y_w \cdot z_w$ and $A = \sum_i S_i \cdot \alpha_i$.

Step 9: Estimation of RT_{60} using ANN

$$RT_{60,ANN} = \text{net}(V, R, \alpha, RT_{60,Sch}) \quad (4)$$

Step 10: Estimation error

$$e_{Sab} = RT_{60,Sch} - RT_{60,Sab} \quad (5)$$

$$e_{ANN} = RT_{60,Sch} - RT_{60,ANN} \quad (6)$$

END $R_{f,c}$
 END $R_{f,b}$
 END $R_{l,r}$
 END z_w
 END y_w
 END x_w

Step 11: Mean square estimation error

$$MSE_{Sab} = \frac{1}{N} \sum_{i=1}^N e_{i,Sab}^2, \quad (7)$$

$$MSE_{ANN} = \frac{1}{N} \sum_{i=1}^N e_{i,ANN}^2. \quad (8)$$

The algorithm was implemented with the following parameters: $W_{min} = 3$ m, $\Delta W = 1$ m, $W_{max} = 10$ m, $H_{max} = 5$ m, $R_{min} = 0.1$, $\Delta R = 0.1$, $R_{max} = 0.9$, $c = 343$ m/s, $T_h = 1.5$ s, $f_s = 44100$ Hz.

RESULTS OF THE EXPERIMENT AND ANALYSIS

A. THE RESULTS

Figures 1. and 3. show the dependence of the estimated values $RT_{60,Sch}$, $RT_{60,Sab}$ and $RT_{60,ANN}$ on the number of rooms n in the learning and testing phases, respectively. Figures 2. and 4. present the estimation errors e_{Sab} and e_{ANN} for RT_{60} during the ANN learning and testing phases, respectively.

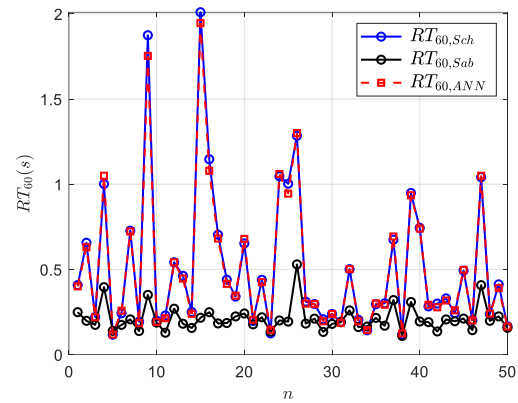


Fig. 1 Dependence of the estimated values $RT_{60,Sch}$, $RT_{60,Sab}$ and $RT_{60,ANN}$ on the number of rooms n during the ANN learning phase.

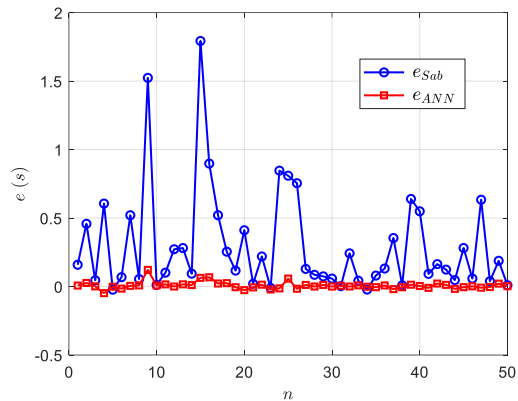


Fig. 2. Estimation errors e_{Sab} and e_{ANN} for RT_{60} during the ANN learning phase.

B. ANALYSIS OF THE RESULTS

Based on the results presented in Figures 1. - 4. and on the numerical values of e_{RT60} and MSE , the following conclusions can be drawn:

a) Learning Phase

The estimated values $RT_{60,Sch}$ (reference) and $RT_{60,ANN}$ show excellent agreement across. The $RT_{60,Sab}$ values exhibit nearly uniform variations, with several abrupt increases (peaks in Fig. 1) that do not fully follow the trend of $RT_{60,Sch}$ and $RT_{60,ANN}$ values and are noticeably lower overall. This indicates the limited accuracy of the Sab_form for the analyzed set of rooms.

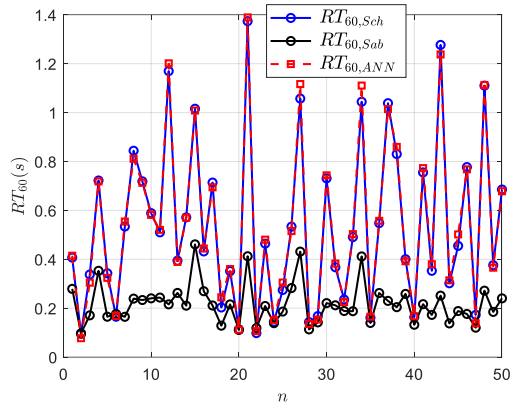


Fig. 3. Dependence of the estimated values $RT_{60,Sch}$, $RT_{60,Sab}$ and $RT_{60,ANN}$ on the number of rooms n during the ANN testing phase.

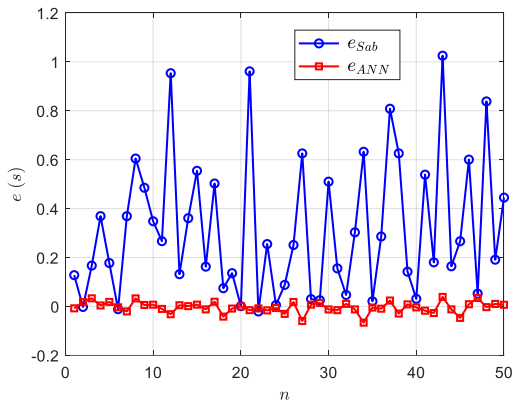


Fig. 4. Estimation errors e_{Sab} and e_{ANN} for RT_{60} during the ANN testing phase.

The estimation errors e_{ANN} are small, stable, and evenly distributed around zero, whereas e_{Sab} are considerably larger, showing pronounced local maxima. Such a distribution indicates the high accuracy of the ANN model during the learning phase and its effective ability to learn the nonlinear relationship between the input parameters and the reverberation time.

For MSE , the following values were obtained:

$$MSE_{Sab,learn} = 0.1786 \text{ and } MSE_{ANN,learn} = 3.9453 \cdot 10^{-4}.$$

The ANN shows a significantly lower mean square error, confirming its high accuracy and efficiency in the learning process.

b) Testing Phase

The reference estimated values $RT_{60,Sch}$ and $RT_{60,ANN}$ also show good agreement, confirming the stability and generalization capability of the network. The $RT_{60,Sab}$ values exhibit more frequent variations, with noticeable abrupt increases (peaks in Fig. 3) that more closely follow the trend of $RT_{60,Sch}$ and $RT_{60,ANN}$ but still deviate significantly from them. This indicates that the limitations of the Sab_form are also present in the testing phase.

The estimation errors e_{ANN} are also very small in this phase, showing only minor deviations from zero, whereas e_{Sab} remain considerably larger with frequent variations.

For MSE , the following values were obtained:

$$MSE_{Sab,test} = 0.1835 \text{ and } MSE_{ANN,test} = 3.9816 \cdot 10^{-4}.$$

The low value of the mean square error in the testing phase also confirms the stable performance and high accuracy of the ANN.

The approximate MSE values in the learning and testing phases indicate the presence of a stable systematic deviation in both estimation approaches. However, this deviation is considerably more pronounced in the RT_{60} estimation using Sab_form, whereas in the ANN it remains minimal and constant, confirming the consistency and high reliability of the estimation.

CONCLUSION

This paper presents the results of an experiment focused on the comparative analysis of reverberation time RT_{60} estimation using the Sabine formula and an artificial neural network ANN.

The reference values obtained by the Schroeder algorithm were used as the basis for evaluating the RT_{60} estimation error of both approaches.

The Sabine formula shows a tendency toward lower estimated RT_{60} values compared to the reference, accompanied by larger variations in the estimation errors, which confirms the limited accuracy of this approach for the analyzed set of rooms.

The ANN demonstrated excellent agreement with the reference values in both the learning and testing phases, with estimation errors close to zero. Nearly identical MSE values were obtained in both phases ($MSE_{ANN,learn} = 3.9453 \cdot 10^{-4}$ and $MSE_{ANN,test} = 3.9816 \cdot 10^{-4}$), which are 452.579 and 460.9394 times lower than the MSE values obtained using the Sabine formula. This confirms the same level of accuracy of the ANN in both the learning and testing phases, as well as the stability of the network performance and the absence of overfitting.

The obtained results confirm that the application of ANN enables a significantly

more accurate and stable estimation of the reverberation time RT_{60} compared to classical acoustic models.

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