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Estimating absorption of materials to match room model against existing room using a genetic algorithm

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Summary
In room acoustic refurbishment/renovation projects, it is common to create a digital room model for use in room acoustic prediction software such as ODEON. Before simulating changes it is desirable to match the model, as well as possible, to existing conditions so that measured room acoustics parameters are in fair agreement with the ones simulated in the digital model. The acoustic data of the surface materials may be imprecise or indeed unknown. Therefore calibration has to be done manually by the room acoustician, who changes the absorption coefficients of the different surfaces in the room model in order to match measured parameters such as EDT, T_{30}, T_S, SPL, C_{50} and C_{80} against the simulated ones in an iterative process. This process is time consuming; requiring many iterations, and even so it can be difficult to obtain a reasonable match. This paper presents an implementation of a calibration tool utilizing a genetic algorithm to search through the M-dimensional search space defined by the number M of the unknown surface materials.

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1. Introduction

The problem of optimizing the absorption coefficients of materials inside an acoustical room model to match with measured data is well-known among room acoustic consultants. This task is usually performed manually in an iterative process. Recently, a method for estimating the absorption coefficients of the surfaces in a room was suggested, based on the inversion of the measured energy decay. The method requires impulse response measurements from 8 omnidirectional microphones [1]. In this paper an application of genetic algorithms is proposed for optimizing the absorption coefficients. The method has been implemented in the ODEON Room Acoustics Simulation software [2]. Assuming that the room has none diffuse conditions, then the room acoustics simulation program should run a number of times using different absorption coefficients as input and analyze the results in order to derive the optimum absorption coefficients. A very simple case would be a room where the same material is applied to all surfaces and one needs to find the absorption coefficient which results in some global reverberation time. If the sound field in the room could be considered perfectly diffuse a room acoustics simulation might not be needed. In fact, the optimization problem could be efficiently solved simply by using bi-sectional search [3] while changing the absorption coefficients. For realistic cases, however, there will typical be 5- 15 materials present in the room and the sound field may be far from diffuse. Indeed this may be what we want to investigate in the first place. So when the absorption has been adjusted we should be able to evaluate acoustic parameters like Early Decay Time EDT, Reverberation Time T_{30}, Center Time T_S, Clarity C_{50}, C_{80} [4], and their variation with source and receiver position. The evaluation needs to be performed for each octave band independently. In the ODEON software absorption data and corresponding simulations are done in eight octave bands from 63 Hz to 8000 Hz. As the search space is multi-dimensional, a bi-sectional search does not seem a feasible solution. Instead, one could simply use a brute force method where a large number of simulations is run using random materials as input (*Monte Carlo* method) and selecting the materials giving the best matching results. However, such an approach seems to converge very slow. Instead of all these methods, in this paper a Genetic Algorithm (GA) is used as one type of search algorithm that is efficient for search in multi-dimensional search spaces (multi-variable problems).

2. Searching for absorption coefficients using a genetic algorithm

Genetic algorithms (GA) are widely used for optimization processes in diverse areas, such as industrial design, artificial life systems and economics. The origins of GA go back to 1975 [6]. GA start with an ensemble of *individuals* (chromosomes) and evolve new and improved individuals by applying principles found in molecular genetics and biology: *crossover* (recombination), *mutation*, etc. In any stage of the evolution the ensemble of individuals is called *population* and corresponds to a *generation*. An individual is essentially a candidate solution to the optimization problem and normally consists of more than one *genes*. The criterion that is used from the evolution process to create an improved generation is the *fitness function*. Properties of the individual that give good fitness between simulated values and target values will have better chances of propagating into the following generations. The reason that GAs have become popular is their ability to find useful solutions in a very complex search space having many minima/maxima without getting stuck in the first occurring local minimum/maximum.

In our optimization problem there are eight different GAs that run independently for each octave band. Translating the foregoing terms to our problem an *individual* consists of a complete set of absorption coefficients for a particular frequency band, corresponding to the different materials in the room. Henceforth we shall use the term *material* for describing its absorption coefficient. One *material* is one *gene*. The terms are shown in Table I. All frequency-dependent GAs start with a random pass (*Monte Carlo* method) where all individuals of the population are generated with absorption coefficients that vary randomly according to a specified range. This can be called 0^{th} generation. After this pass the evolution process is initiated by filtering out the best individuals as parents and producing children that are likely to inherit some of the advantages from their parents. During this process the initial random absorption coefficients are constantly modified according to genetic operators, as described in section 2.3.

2.1. Target value and fitness function

In order to evaluate how well a room simulation model with a given set of materials (an individual) matches against the measured room one needs a *fitness function* (see Table I). The *fitness function* returns a number (fitness) to the GA that allows it to determine which individual (candidate solution) is better than others, controlling the genetic evolution. In our problem the GA seeks for individuals that minimize the fitness value, while in other GA problems the criterion might be a maximization of the fitness. In principle it can be considered to evaluate directly how well the simulated impulse responses match against the measured ones. However, there is bound to be differences between them as neither measurements nor simulations are perfect [7]. Instead, we have chosen to compare how well some of the room acoustic parameters match - as these are supposed to be good measures for important attributes of the acoustics in a room. Indeed, the room acoustic parameters are one of the most important tools for the room acoustician. In order to evaluate the fitness of a set of materials, point responses for a number of source-receiver pairs are simulated and the average deviation of a number of room acoustic parameters is calculated. The parameters are normalized to their JND (Just Noticeable Difference)[4] (e.g. 5% for reverberation time and 1 dB for C_{80}) so it is possible to merge different parameters into one fitness number. If the difference between measured and simulated parameter is less than 1 JND - e.g. less than 1 dB for C_{80} - this is fairly accurate as it is not possible for the human receiver to perceive the difference subjectively. The fitness function used is given by the following formula:

$$\epsilon[JND] = \frac{\sum_{k=1}^{K} \sum_{i=1}^{I} |[Par_i^k]_{Sim} - [Par_i^k]_{Meas}|}{K \cdot I}, \quad (1)$$

where ϵ is the fitness value (error between simulated and measured value), and $[Par_i^k]_{Sim}$, $[Par_i^k]_{Meas}$ represent the simulated and measured acoustic parameter i for the source-receiver combination k. K is the total number of source-receiver combinations, while I is the total number of used acoustic parameters.

Table I. Terms used in GA and their interpretation to our acoustic problem.

GA terms	Analogue to material optimization
Gene	Absorption coefficient of a material for a specific band.
Chromosome	Set of genes (materials) that characterize an individual.
Individual	A candidate solution that consists of a list of genes (materials) (associated to a chromosome).
Population	Ensemble of Individuals - all different material combinations for one generation.
Generation	A stage in the evolution process corresponding to a population.
Evolution	Process of obtaining new sets of materials.
Target	Measured acoustic parameters.
Fitness	The error between simulated and measured data for an individual. Should be minimized.
Fitness function	Calculation of *fitness* according to equation 1.

2.2. Search Space

In order to optimize the search process it is important to limit the search space. The search space can

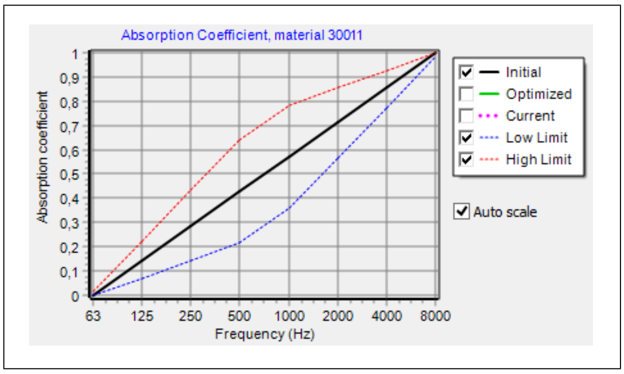

Figure 1. Graph in the ODEON utility displaying the 50% search range for a material having absorption coefficients linearly from 0 at 63 Hz to 1 at 8000 Hz.

be limited by telling the GA that some of the absorption coefficients should only vary within certain limits and indeed that some should not be changed at all. This variation can be called *search range* and is given in percentage. A value of 100% would lead to a search range from 0 to 1 absorption coefficient, regardlesss the initial values. A value of 0% leads to no change at all, meaning that the material is exlculded from the optimization process. A search range between 0 and 100% gives lower and upper limits depending on the initial ansorption coefficient. Figure 1 shows an example of limits for 50% range. Careful estimation of the search range is crucial for achieving realistic solutions. For example if it is suspected that two hard parallel walls may cause a flutter echo once extra absorption is installed in the refurbished room, then it is important to restrict the absorption coefficients and search range to low values e.g. maximum 2%. If a material is only installed on a small surface area or it is believed to be well known it should be assigned a search range of 0%. Omitting some materials from the optimization process will reduce the calculation time as the number of individuals has a linear influence on it. By limiting the range of absorption coefficients the search process also becomes more efficient as the GA will only search where there are possible valid solutions - e.g. if it is known that there is mineral wool in the ceiling, the GA should not specify absorption corresponding to wooden floor and vice versa. This will not only make the search faster, but it will also prevent unrealistic solutions which match the target well but they are obviously wrong (wooden floor on the ceiling and mineral wool on the floor). It is recommended that the user initially assigns materials as realistic as possible. In the ODEON calibration utility it is possible to assign a search range between 0 and 100% to each material.

2.3. Genetic Algorithm parameters

Apart from the fitness function and the search range described in sections 2.1 and 2.2 respectively, a number of evolution parameters have to be set, which affect the efficiency and accuracy of the GA.

The *selection method* determines the way individuals are selected from the current generation to produce children of the next generation. Four of the most common selection methods are *Roulette*, *Random*, *Tournament* and *Elitist*. According to the *Roulette* selection method, parents are selected based on a roulette-wheel. The parents with the best fitness are assigned a bigger portion on the wheel and hence they are more likely to be chosen. This portion-based approach can lead to small variance in fitness and low selective pressure [5]. A widely used solution to the problem is to rank the fitness values and assign the roulette portions according to the rank number. In the *Random* method parents are selected completely randomly. In the *Tournament* method a few individuals are selected randomly from the whole population and only the best are kept. This is repeated several times until a specified number of the best individuals is collected. With the *Elitist* method the top n percent of the population is chosen and re-chosen. In the present absorption coefficient optimization algorithm the *Elitist* method has been used, which seems to provide meaningful results faster than the other methods. At the end of each generation the best 50 % of the parents are chosen to make new children.

The *population* of individuals, which is presented in Tab.I, is also an important parameter that affects the speed of the algorithm and the convergence. Values that are multiples of the number of materials can be used. It has been found that for our specific problem 4 individuals per material is a reasonable number.

In the ODEON optimization utility the user can define the probabilities of three genetic operators which control the way chromosomes from parents are combined to derive children of the next generation. Data inside the GA are represented in binary mode. This means that absorption coefficients are encoded into strings of bits (0 and 1) with varying accuracy, determined by the number of bits in the strings. For the present paper strings of 16 bits were used. The way absorption coefficients (real numbers) are represented in binary mode makes the application of the genetic operators more straightforward. The *crossover* operator determines which portions of two parents will be combined to create two new offspring. The *inversion* operator reverses a segment of a chromosome. Finally the *mutation* operator mutates the state of a bit (between 0 and 1 values). The most common value for the *mutation* probability is 1 divided by the string length, which means that only one bit from the string is allowed to change state [5].

Figure 2 shows the basic structure of the proposed GA optimization method summing up the elements presented in section 2.

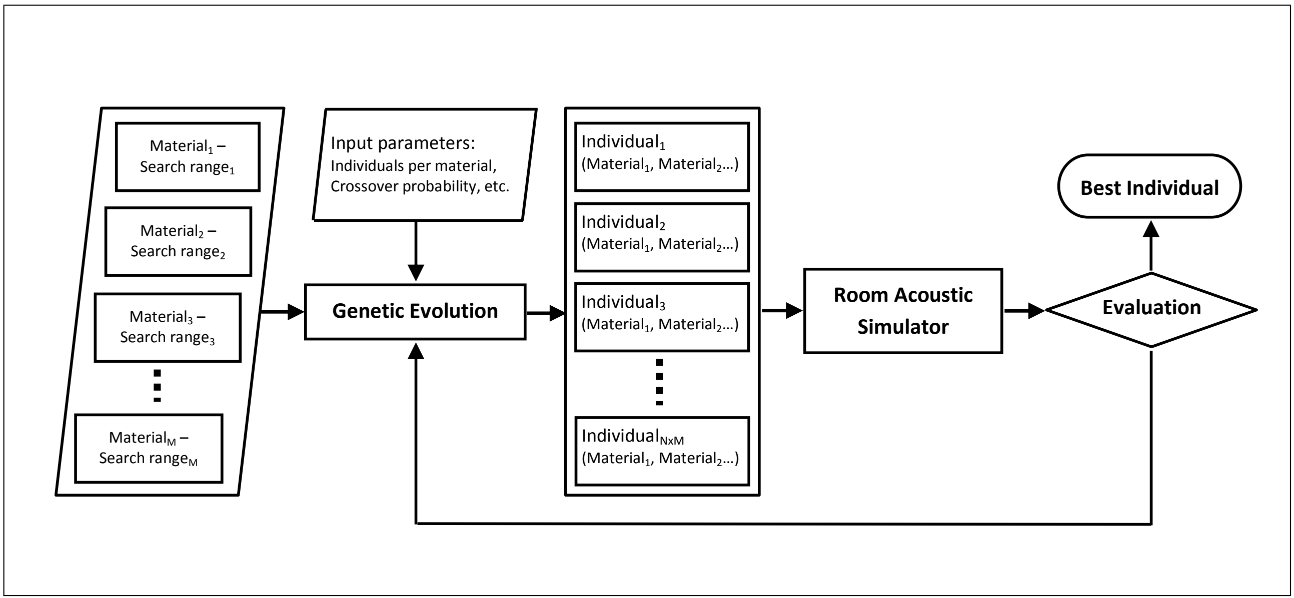

Figure 2. Flow chart of the proposed GA optimization method. A sufficient population is needed for the algorithm to find a solution. The population is defined by N individuals per material, so that the total number of individuals in the population is $N \times M$.

3. Application to a case

The optimization method proposed in this paper was applied for calibrating the materials in a model of Auditorium 21 at the Technical University of Denmark (DTU), which is shown in Figure 3. The room was also used as example in [7]. The initial assignment of materials is listed in table II. There are 11 different materials and most of them have been selected as from the standard material library of ODEON. The back wall which is some kind of resonator panel with unknown resonance frequency and ceiling was set to 60% absorption for all frequencies. It was not possible to inspect the ceiling material so an initial estimate was 2 x 13 mm gypsum board with mineral wool back.

The fitness was calculated as an average over 10 source- receiver pairs (2 sources and 5 receivers), according to equation 1. Initially, materials were optimized taking into account only the reverberation time T_{30}, which is an acoustic parameter that gives a good overlook of the decay process in the room. Afterwards the same optimization was carried out for seven room acoustic parameters: EDT, T_{15}, T_{20}, T_{30}, T_S, C_{50} and C_{80} which have a high degree of complementarity among them. For example, typically as T_{30} increases, C_{80} decreases and vice versa. This makes the GA fitting process more difficult in an attempt to balance counter forces.

3.1. Matching only one parameter

Reverberation time T_{30} was chosen in this case as the unique target acoustic parameter. Equation 1 was used to for calculating the average error (fitness) between measured and simulated values for the ten source-receiver pairs. For each material 4 individuals have been used, which leads to a population of 44 individuals. In Figure 4 the convergence process of the GA is shown. The search range was set to 100% for all materials, allowing no constrains during the search proccess. This means that the algorithm has a broad range to search for the best solution, leading to a greater chance of finding an individual that minimizes the error in equation 1 than when using smaller ranges.

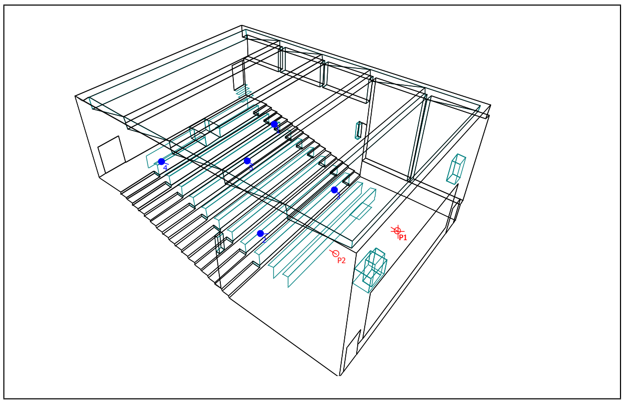

Figure 3. The Auditorium 21 at the Technical University of Denmark (DTU), as it looks inside ODEON, with two sources (in red) and five receivers (in blue).

At the end of the random (Monte Carlo) round (0^{th} generation) the fitness values are very high for most of the frequencies. During the next generations the values decline dramatically until a very satisfying convergence is achieved at around 9^{th} and 10^{th} generations. Apart from the lowest two octave bands all other fitnesses remain well below 1 JND.

Table II. Initial choice of materials in the model of Auditorium 21. For each material, the octave-band dependent absorption coefficients are given together with the area occupied by the material.

	Frequency (Hz)								
Material	**63**	**125**	**250**	**500**	**1000**	**2000**	**4000**	**8000**	**Area (m^2)**
80% flat absorption - strips on ceiling	0.800	0.800	0.800	0.800	0.800	0.800	0.800	0.800	13.8
Plasterboard 13mm on frame - ceiling	0.300	0.300	0.120	0.080	0.060	0.060	0.050	0.050	217.1
Smooth concrete, painted - floor	0.010	0.010	0.010	0.010	0.020	0.020	0.020	0.020	24.5
16-22 cm wood facing - wall	0.250	0.250	0.150	0.100	0.090	0.080	0.070	0.070	236.6
Wooden floor on joists	0.150	0.150	0.110	0.100	0.070	0.060	0.070	0.070	187.6
Solid wooden door	0.140	0.140	0.100	0.060	0.080	0.100	0.100	0.100	23.8
30 % flat absorption - wall	0.300	0.300	0.300	0.300	0.300	0.300	0.300	0.300	7.4
Double glazing - windows	0.100	0.100	0.070	0.050	0.030	0.020	0.020	0.020	46.1
Wooden table - audience tables	0.020	0.030	0.040	0.050	0.070	0.080	0.080	0.090	100.8
Smooth unpainted concrete - blackboard	0.010	0.010	0.010	0.020	0.020	0.020	0.050	0.050	25.0
60% flat absorption - backwall	0.600	0.600	0.600	0.600	0.600	0.600	0.600	0.600	54.9

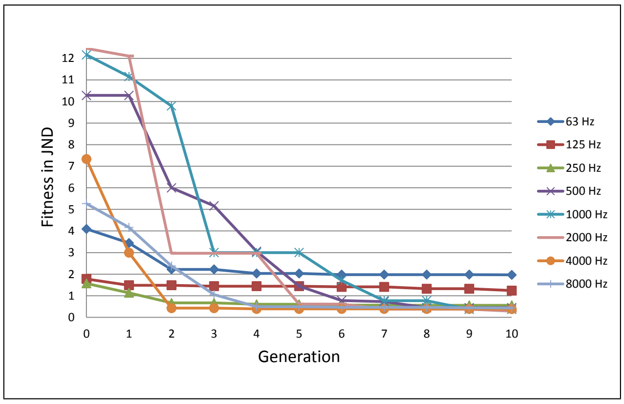

Figure 4. Best fitness value in JND at the end of each generation. Absorption coefficients in this case are assigned a 100 % search range.

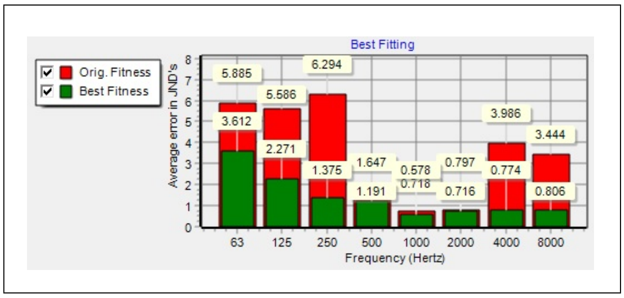

Figure 5. Best fitness values, together with the original fitnesses corresponding to table II. The best fitnesses were derived by running the optimization algorithm for 10 generations with a search range of 100%. The fitness is an average from 10 source-receiver pairs and 7 parameters, using equation 1.

3.2. Matching seven acoustic parameters

Now equation 1 is applied for seven parameters: EDT, T_{15}, T_{20}, T_{30}, T_S, C_{50} and C_{80}. Initially the search range was set to 100% for all the materials. Figure 5 shows the average fitness for each octave band before the calibration process, along with the best fitness as they converged after ruuning the calibration method for 10 generations. It is clearly seen that the method was able to provide a very satisfying solution in terms of average fitness value, but the individual absorption coefficients did not lead to realistic materials in most of the cases.

In the next step the ceiling material and the backwall material were given a search range of 80% and all of the rest materials were assigned a search range of 50%. Limiting the search range to 50% ensures that no matter the changes, the shape of the frequency-dependent absorption coefficient remains the same and closer to reality. It is worth mentioning that the narrower the search range, the less generations it takes for the algorithm to converge to a solution. This time 8 generations were used. The optimized absorption coefficients with this approach are given in table III. In principle when the octave band absorption coefficients of a material change the name should change too, as the optimized material can be significantly different from the original material. However, since we can treat this process as a fine tuning of the existing materials we have chosen to keep the original names as references for the optimized ones.

In Figure 6 the average error for each octave band is shown before the calibration process along with the errors after. As can be seen, the error has been reduced significantly for all octave bands; for the bands 500 - 8000 Hz the error is close to or well below 1 JND. For the octaves, 63 - 250 Hz the error is more significant, almost 5 JND at 63 Hz. However, if inspecting the differences between measured and simulated parameters at those frequencies it turns out that, although the variation with position is not caught accurately, the parameters averaged over positions match fairly well for some parameters. It therefore seems that smaller error number at the lowest octaves cannot be achieved because the energy based simulation in ODEON does not include phase information and modal behavior, which might be present in the real room. This is indeed confirmed when comparing the measured and simulated decay curves at 63 or 125 Hz (see Figure 8 or 10).

Table III. Optimized materials in the model of Auditorium 21. For each material, the octave-band dependent absorption coefficients are given together with the area occupied by the material.

	Frequency (Hz)								
Material	**63**	**125**	**250**	**500**	**1000**	**2000**	**4000**	**8000**	**Area** (m^2)
80% flat absorption - strips on ceiling	0.719	0.850	0.766	0.703	0.848	0.767	0.756	0.829	13.8
Plasterboard 13mm on frame - ceiling	0.580	0.573	0.297	0.057	0.125	0.117	0.198	0.190	217.1
Smooth concrete, painted - floor	0.028	0.018	0.014	0.019	0.035	0.041	0.040	0.036	24.5
16-22 cm wood facing - wall	0.142	0.244	0.150	0.093	0.078	0.099	0.086	0.097	236.6
Wooden floor on joists	0.214	0.225	0.137	0.152	0.063	0.032	0.075	0.114	187.6
Solid wooden door	0.158	0.117	0.113	0.033	0.068	0.054	0.114	0.063	23.8
30 % flat absorption - wall	0.386	0.356	0.341	0.405	0.398	0.240	0.211	0.272	7.4
Double glazing - windows	0.088	0.083	0.058	0.078	0.044	0.017	0.036	0.014	46.1
Wooden table - audience tables	0.042	0.055	0.060	0.084	0.068	0.124	0.126	0.144	100.8
Smooth unpainted concrete - blackboard	0.027	0.008	0.014	0.030	0.018	0.011	0.084	0.071	25.0
60% flat absorption - backwall	0.264	0.408	0.656	0.516	0.273	0.258	0.272	0.365	54.9

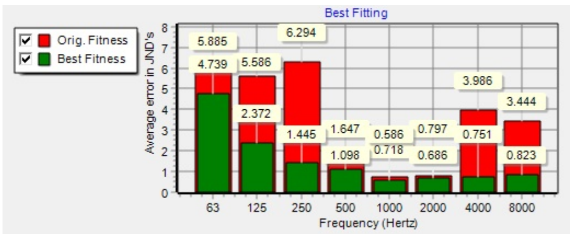

Figure 6. Best fitness values corresponding to the optimized absorption coefficients of table III, along with the original fitnesses corresponding to the absorption coefficients of table II. The best fitnesses were derived by running the optimization algorithm for 8 generations. The fitness is an average from 10 source-receiver pairs and 6 parameters, using equation 1.

Figures 7 to 10 illustrate some examples of simulated and measured acoustic parameters before and after the material calibration process. The graphs are taken directly from the *Multi-point Response* display in ODEON [2]. On the left side of the display the results for all receivers at a specific band are shown, while the right-side graph presents the results for all bands at a particular receiver position. Among the numerous combinations of *Multi-point Response* graphs we have chosen to include some representative ones, that show a large initial error between the simulated and measured values. The correction of EDT in Figure 7 has been very satisfying, despite the fact that EDT is a very sensitive parameter, highly affected by the fluctuations of the initial part of the impulse response. The matching of T_{30} (Figure 8) is quiet successful for all frequencies except from 63 Hz, probably due to the low frequency limitations of the software, mentioned above. The results for T_S are shown in Figure 9 for all receivers at 250 Hz and for receiver 5 at all bands. The agreement after the optimization process is very good for all bands at receiver 5, even at the lowest ones. Moreover the values at all receivers have been improved significantly at 250 Hz, which can be considered a low band. Finally, a C_{80} graph is displayed in Figure 10. A low octave band (125 Hz) has been chosen for displaying the results at all receivers. On average the agreement is better after the calibration although some noticeable deviations remain at some positions. In general the results have been improved for all bands of receiver 1.

4. Computational performance

In our setup we used 2 source and 5 receiver positions. 11 materials were calibrated. 4 Individuals were used per material, leading to 44 individuals in the population of each generation. The calibration seemed to stabilize after the 8th generation for the second round of calculations in section 3.2. To carry out the above calibration required 2 x 5 x 11 x 4 x (8+1)=3960 point response calculations. So it is obvious that a point response calculation needs to be fast to provide solutions within practical time. On the other hand, if simulation parameters - such as number of rays - are not defined carefully in order to achieve realistic results, then the calibration may not make much sense. The calibration procedure including all 3960 point response calculations and using 2000 late rays [2] took about 30 minutes on an Intel CoreTM i7 CPU, running at clock speed of 3.4 GHz (utilizing 4 cores). Thus we do consider the calibration utility in ODEON fast enough to be a useful tool.

5. CONCLUSIONS

A utility that allows matching materials in a digital room acoustic model against the real room has been implemented inside the room acoustics program ODEON. The utility, which is based on Genetic Algorithms (GA), allows optimizing multiple materials in the same model and is capable of significantly reducing the deviation between measured and simulated acoustic parameters over a number of source-receiver pairs. An application of the method to an existing

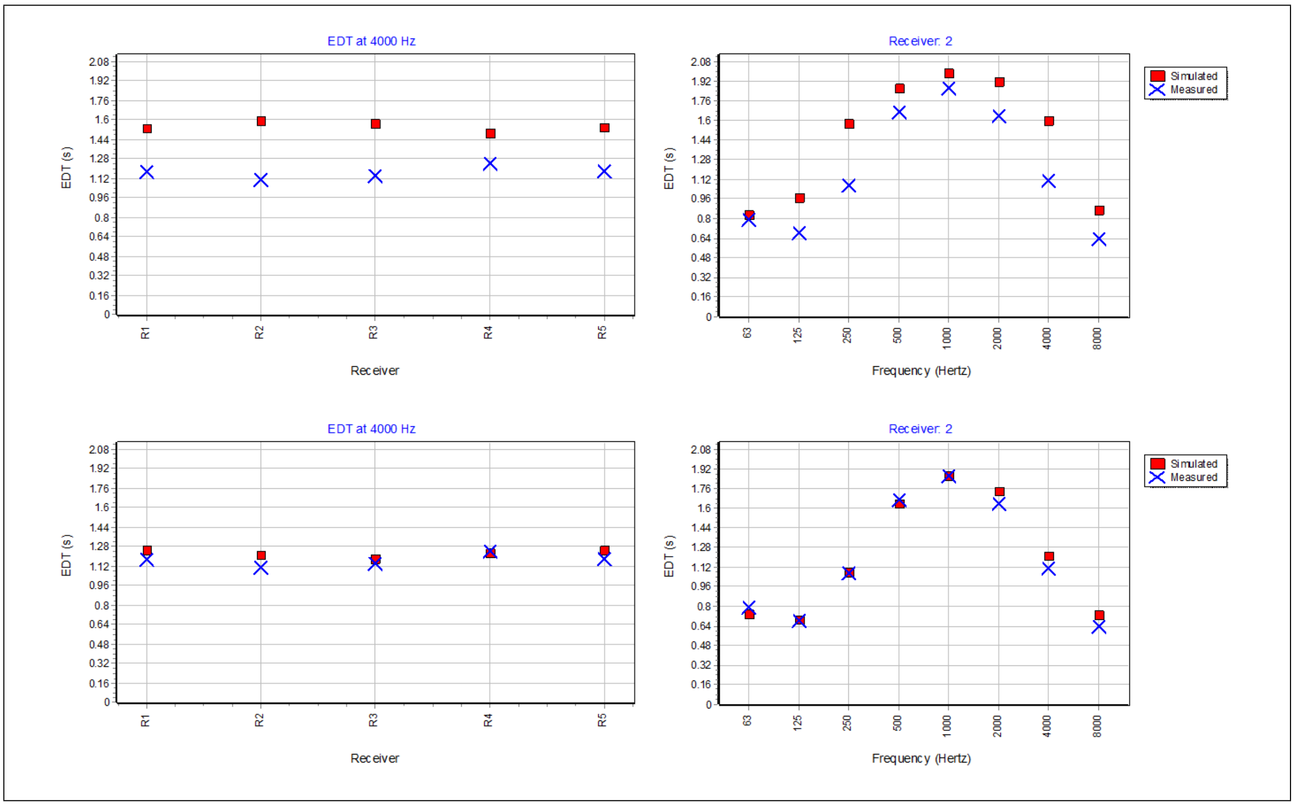

Figure 7. Early Decay Time, *EDT*, as shown in ODEON for 5 Receivers at 4000 Hz and for Receiver 2 at all bands. *Upper graph*: Simulated versus Measured before calibration. *Lower graph*: Simulated versus Measured after calibration.

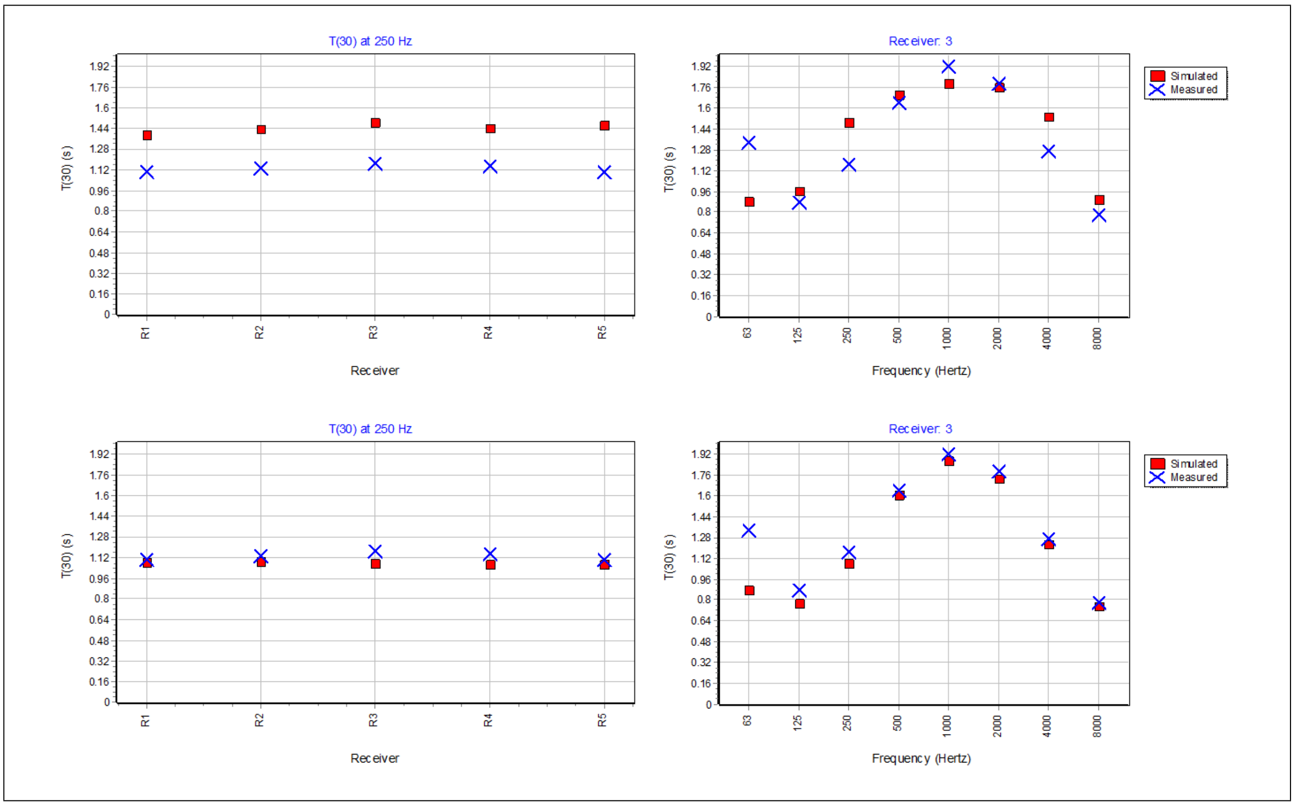

Figure 8. Reverberation Time, T_{30}, as shown in ODEON for 5 Receivers at 250 Hz and for Receiver 3 at all bands. *Upper graph*: Simulated versus Measured before calibration. *Lower graph*: Simulated versus Measured after calibration.

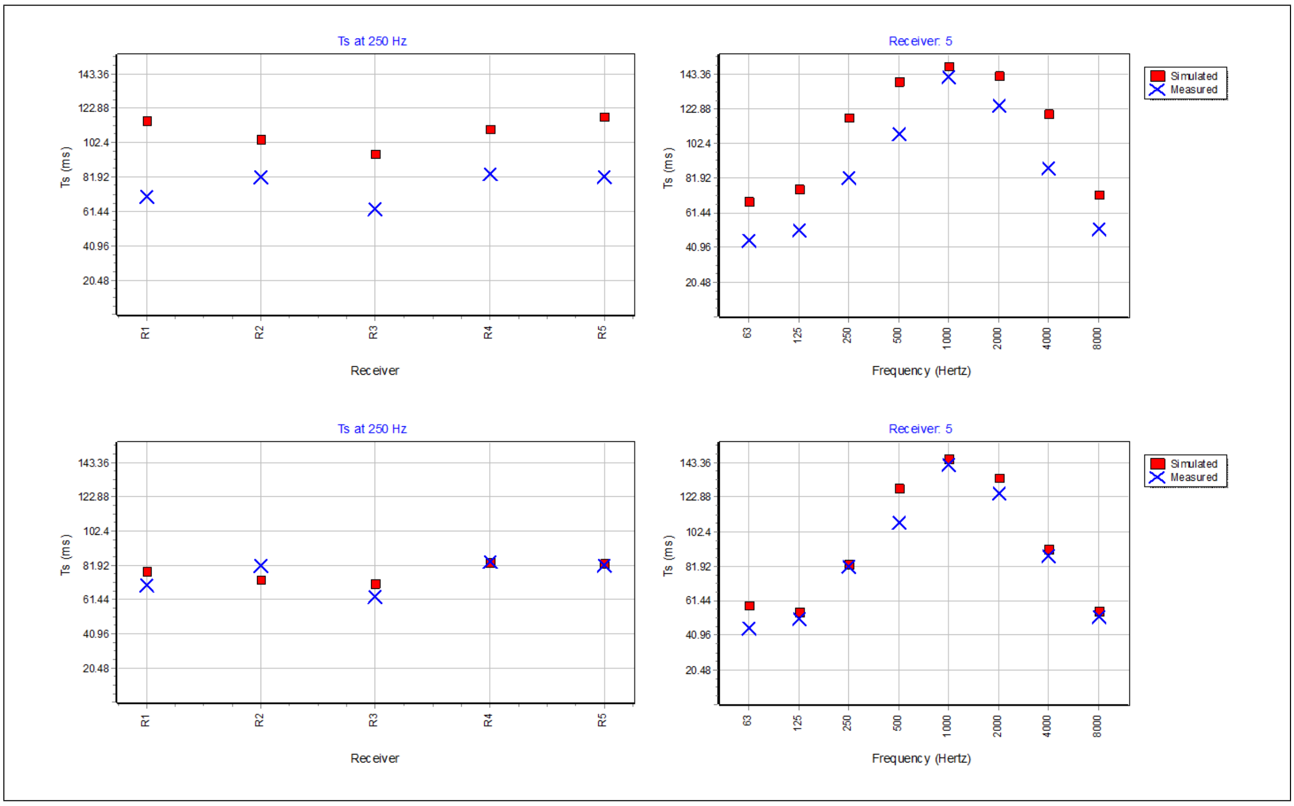

Figure 9. Center Time, T_S, as shown in ODEON for 5 Receivers at 250 Hz and for Receiver 5 at all bands. *Upper graph*: Simulated versus Measured before calibration. *Lower graph*: Simulated versus Measured after calibration.

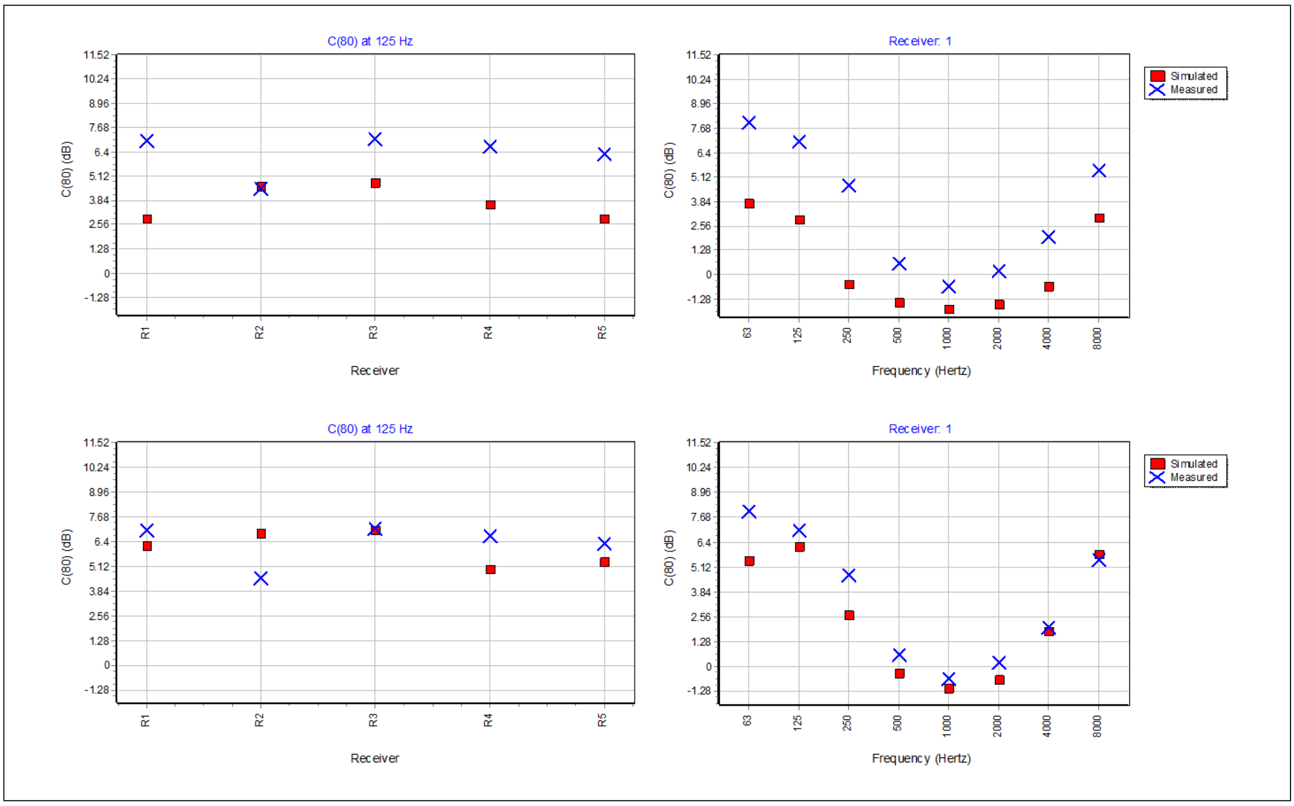

Figure 10. Clarity, C_{80}, as shown in ODEON for 5 Receivers at 125 Hz and for Receiver 1 at all bands. *Upper graph*: Simulated versus Measured before calibration. *Lower graph*: Simulated versus Measured after calibration.

auditorium was presented. The algorithm performed very satisfactory. For all eight octave bands the average error is reduced significantly (from 6.3 JND's to 1.4 JND's at 250 Hz) and for the 500 - 8000 Hz bands the resulting error is equal to or below 1 JND, which is quiet satisfactory. For the low octave bands 63 - 125 Hz the optimization is also significant but the error remains important, probably because modes of waves are not included in the energy based simulation model. Another possible explanation may be the frequency dependent scattering coefficients assigned to the surfaces. In the present work fixed scattering coefficients were used in the model, varying from 0.05 to 0.3. However in a future work the scattering coefficients could be optimized in same way as the absorption coefficients. It has been found that it is important to apply realistic search ranges for each absorption material, in order to get realistic optimized solutions. The utility includes tools that make it easy to specify search ranges for each material.

The method suggested in this paper can also be used to optimize materials towards a specified theoretical target. For example, one could try to search for the best combination of materials that give certain reverberation time and clarity in a room. In such a case the term $[Par_i^k]_{Meas}$ in equation 1 can be replaced by $[Par_i^k]_{Target}$. Still correct estimation of initial materials and search ranges is important to encourage an effective convergence.

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