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5aAAb5. Optimal design of sound reflectors by particle swarm optimization

Yuuki Tachioka*

***Corresponding author's address: Nihon University, 3-6-13-E612 Fujisawa, Fujisawa, 251-0052, Kanagawa, Japan, yuuki_tachioka@yahoo.co.jp**

Room-acoustical design requires careful consideration of the room shape and the materials used, in addition to in-depth experience. Numerical analyses can reduce the burden placed on designers by automatically generating many room candidates and selecting an optimized design that is based on objective measures. While many researchers are currently studying numerical analytical methods, further research of investigating optimal design methods is needed. This paper investigates an optimal design method that facilitates efficient acoustical design by combining geometrical acoustic simulation with an optimization technique known as particle swarm optimization. While the eventual objective of this research is global acoustical design, this paper is limited to designing local shape. Local shapes are important because they affect the characteristics of the global sound field. This paper addresses the design of sound reflectors, which, scatter initial reflections of sound waves to the entire acoustic field. Consequently, the optimization variables are the shapes and materials of the sound reflectors and the objective function evaluates the uniformity of a sound field in terms of the room-acoustic indexes (T20, C80, Ts). The experiment shows that the optimized sound reflectors achieve more uniform room-acoustic indexes than the original reflectors.

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INTRODUCTION

In designing spaces with particular acoustical requirements (e.g., concert halls), specifications, such as the room shape and the materials used, must be considered. Neglecting these features in the design can create both physical and psychological problems. Physical problems include the concentration of reflected sounds at a specific receiving point or echoes because of multiple reflections. Psychological problems include the perception of reverberations as undesirable. In current practice, various candidate specifications are typically enumerated based on the designers' experience, from which a design is selected using a simple reverberation formula or geometrical acoustic simulations. Real models may be fabricated for the selected some candidates and final specifications designated. The selection of an optimized solution among multiple (but not many) candidates that have been designed from experience requires a high quality for the initial candidates and sufficient design experience. Moreover, unoptimized solutions may be selected by this process.

In contrast, the burden on a designer can be reduced by generating many samples automatically, among which an optimized design is selected using numerical simulation based on objective measures. The recent expansion in computer resources has resulted in a reasonable computational time of the echo time patterns for thousands of candidates, which therefore represents an effective approach. Further research is needed to develop efficient techniques for selecting an optimized design among many candidates, to augment various studies on improving computational accuracy [1, 2, 3] and reducing the computational load [4] of acoustic simulations. An established and user-friendly optimization design method can enable even inexperienced designers to use acoustic simulations.

Optimization problems for radoms, which include antennas, are encountered in electromagnetics [5, 6]. Radoms need to meet appropriate specifications for incident waves from arbitrary angles. Designing the shape, thickness and materials of radoms to specification is challenging. Combination of geometrical optics analyses with the optimization technique called "particle swarm optimization" (PSO) [7] can produce an optimal radom design that meet specifications [6].

An optimization method is combined with numerical acoustic simulation in this paper. Although the ultimate objective of this research is the design of the entire space, the shapes of components in the space are optimized in this paper because only a small number of parameters need to be optimized and it is well known that components in the space, even small components, affect the characteristics of the entire sound field. This paper focuses on acoustic reflectors. These reflectors are installed on the ceilings of halls to scatter the initial reflected sounds that support direct sounds. Although limited aspects of these shapes are validated with wave acoustic simulations [8, 9], reflector shapes are usually designed based on experience. In this paper, reflector shapes are determined using several variables. Then the shape is optimized by combining acoustic simulation with PSO. This process for the optimal design of components in the space may be extended to the design of the entire space in the future.

PRINCIPLE OF PSO

Optimization problems determine the optimized solution $\mathbf{r}_{\text{opt}}$ that maximizes the objective function $F(\mathbf{r})$ of a vector $\mathbf{r}$ under constraints, where $\mathbf{r}_{\text{opt}}$ is defined as

$$\mathbf{r}_{\text{opt}} = \arg\max F(\mathbf{r}). \tag{1}$$

Optimization problems can be classified into convex and non-convex problems [10]. Convex problems are comparatively easy to solve by the stochastic descent method, whereas non-convex problems are difficult to solve because of the existence of multiple local optima. Shape design is a non-convex problem in many cases because multiple local optima exist.

PSO is an efficient optimization technique for non-convex problems that emulates biotic behaviors, such as genetic programming (GP) [7], for which many studies have been conducted thus far. PSO outperforms GP in many cases. PSO designates candidates for the optimized solutions (the particles) and for a group of particles (a swarm). As a swarm of birds or fish moves in the same direction although each bird or fish (particle) has its own individual motion, the interaction between the particles and a swarm guides the particles toward the optimized solution. PSO updates the solutions from randomized initial states toward the optimized states, similar to GP. Unlike GP, there is no system of intersection and mutation in PSO; instead, to prevent the solution from being trapped in a local optimum by optimizing each particle separately, the relation between the particles and the swarm constrains the motion.

In PSO, particles move in the Q-dimensional space that is associated with the variables to be optimized. Each particle has a Q-dimensional coordinate vector r and a velocity vector v. An initialization procedure assigns random values to the particles within the definition area. An iterative procedure steers the particles toward the optimized solution, as described below. The i particle coordinates and velocity vectors at the k^{th} step are denoted by $\mathbf{r}_i^k$ and $\mathbf{v}_i^k$. Those at the next ($k^{\text{th}}+1$) step are given as

$$\mathbf{v}_i^{k+1} = \gamma \mathbf{r}_i^k + c_1\eta\left(\mathbf{r}_{\text{best}(i)}^k - \mathbf{r}_i^k\right) + c_2\eta\left(\mathbf{r}_{\text{best}}^k - \mathbf{r}_i^k\right), \tag{2}$$

$$\mathbf{r}_i^{k+1} = \mathbf{r}_i^k + t\mathbf{v}_i^{k+1}, \tag{3}$$

where $\mathbf{r}_{\text{best}(i)}^k$ denotes the optimal solution of particle i ($1 \le i \le n_p$) after k ($0 \le k < k_{max}$) iterations and $\mathbf{r}_{\text{best}}^k$ denotes the optimal solution of the swarm. The inertial weight γ (over [0,1]) balances the local and global optimal solutions [11] and c_1 and c_2 denote the constants that represent the confidence on the particles and the swarm, respectively. The randomized value η (over [0,1]) provides a mutation-like system of GP. The first term of Eq. (2) corresponds to an inertial term, while the second and third terms serve to find the local and global optimal solutions, respectively. The particles are attracted by both their own optimal solutions $\mathbf{r}_{\text{best}(i)}^k$ and the swarm optimal solution $\mathbf{r}_{\text{best}}^k$. The farther the particles are from the swarm optimal solution, the larger is the velocity of motion $\mathbf{v}_i$, which indicates a stronger attraction to the optimal solution.

In this paper, local optimizations are prevented by starting optimizations from three initial states. The optimization process is summarized below:

1. The initial state is set at $k = 0$ by assigning random values to the initial optimization variables $\mathbf{r}_i^0$.
2. The objective functions $F(\mathbf{r}_i^k)$ are calculated for all particles.
3. The objective function $F(\mathbf{r}_i^k)$ of the particle i is maximized by updating the optimized solution of the particle $\mathbf{r}_{\text{best}(i)} = \arg\max_k F(\mathbf{r}_i^k)$.
4. The objective function $F(\mathbf{r}_i^k)$ of the swarm is maximized by updating the optimized solution of the swarm $\mathbf{r}_{\text{best}} = \arg\max_{k,i} F(\mathbf{r}_i^k)$.
5. The coordinate vectors $\mathbf{r}_i^{k+1}$ and velocity vectors $\mathbf{v}_i^{k+1}$ of all particles are updated at the next step by using Eqs (2) and (3)
6. If k is less than the designated number k_{max}, k is increased by one and the procedure returns to step 2 and the iteration continues.

APPLICATION OF PSO TO THE DESIGN OF ACOUSTIC REFLECTORS

To apply PSO to acoustical design problems, the acoustical design must be formulated as an optimization problem (i.e., the properties of the objects are parameterized by designating the optimized variables r and the objective function F, which represents the acoustic condition). Each particle represents an acoustic field, corresponding to a variable r. A swarm is a group of n_p particles.

First, the optimized variables r must be determined. In this paper, the most general reflectors fixed from the ceiling are assumed (e.g., the variables for the reflectors are shape, height, area, inclination, and material of the reflectors). The reflector shape is given by Eq. (4), which is a generalization from the study in [8]. Figure 1 shows examples of reflectors. The reflector footprint is 0.6 m×0.6 m. The variables to be optimized are θ[°] and β, where x', y' and z' denote the local coordinate system relative to the origin at the center of each reflector (x_c, y_c, z_c). The local coordinates for each reflector satisfy the following relationship:

$$z' = \frac{0.6}{\sin(\theta)} - \left(\beta\sqrt{\left(\frac{0.6}{\sin(\theta)}\right)^2 - x'^2} + (1-\beta)\sqrt{\left(\frac{0.6}{\sin(\theta)}\right)^2 - y'^2}\right), \tag{4}$$

where $x' = x - x_c$, $y' = y - y_c$, and $z' = z - z_c$. The reflector shape (β, θ) and the reflector scattering coefficient as mentioned in the experimental setup are represented by r. For simplicity, the optimized variables are limited to two or three variables in this paper. This approach can be applied to any number of optimized variables r but too many variables can negatively affect the convergence of the optimization. After limiting the optimization to a certain number of parameters, some optimal parameters will already be known and the remaining parameters should be optimized. Such a hierarchical approach is suitable for the problem at hand. Actually, in the model experiments, a limited number of parameters are validated step by step.

Next, the objective function F is determined. The function of a reflector is to scatter the high-energy initial reflections that support direct sounds to many points and to prevent the concentration of reflections at specific points. Acoustic problems are likely to occur if there are big differences between the room acoustic indexes at the receiving points and those at points nearby. The variances of the room acoustic indexes should be sufficiently small to prevent such an occurrence. In this paper, the objective function is the sum of the inverse of the standard deviation σ of three room indexes (the reverberation time (T_{20}), the clarity (C_{80}), and the center time (T_s)) at each receiving point:

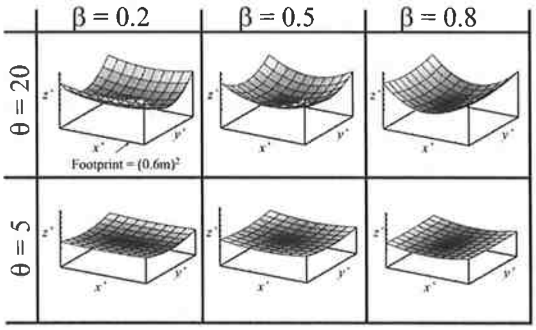


FIGURE 1: Examples of acoustic reflectors.

$$F(\mathbf{r}) = \frac{1}{\sigma(T_{20})} + \frac{1}{\sigma(C_{80})} + \frac{1}{\sigma(T_s)}. \tag{5}$$

This objective function F motivates an optimization solution which homogenizes these room acoustic indexes in the receiving area. Although T_{20}, C_{80}, and T_s are in different ranges and may require normalization, the absolute values of F are not very significant in this case. The optimization of the components in the space affects the variance of the room acoustic indexes rather than the mean of these indexes. Therefore, the variance becomes the focus of the optimization. The objective function set arbitrarily and any objective function may be used that fulfills the desired goals. The concrete procedure follows:

1. The random initialized values are denoted by $\mathbf{r}_i^0$ $(1 \leq i \leq n_p)$. These values must be located within the definition areas. The value of k is initialized to zero.

2. Substituting $\mathbf{r}_k$ (β, θ) into Eq. (4) generates n_p reflectors with scattering coefficients (where each reflector corresponds to a particle, i.e., n_p particles), which are analyzed by a geometrical acoustic simulation. Many particles are not needed (generally 20-30 particles are used) because the particles move within the definition area.

3. The room acoustic indexes (T_{20}, C_{80}, and T_s) mentioned above are calculated using the obtained echo time patterns.

4. The objective function $F(\mathbf{r})$ is calculated using the calculated room acoustic indexes.

5. If k is less than k_{max}, the next step $\mathbf{r}_{k+1}$ is calculated by Eqs (2) and (3); then k is increased by one and the procedure returns to step 2.

EXPERIMENTS

In this paper, a combination of a geometrical acoustic simulation with PSO are used for optimal design. While wave acoustic simulation is currently studied in academic research, geometrical acoustic simulation is widely used in practice because of its low computational load. The iterative nature of optimization techniques results in an excessive computational cost in a wave acoustic simulation (e.g., for PSO with a set of n_p $(= 20)$ particles and k_{max} $(= 100)$ iterations. Totally 2000 acoustic simulations are needed). Though the developed method cannot be applied to wave-based problems, such as interference, the method can be applied to wave acoustic simulations or model experiments using an identical procedure to that detailed here. If the computational load of wave acoustic simulations becomes practical in the future, the acoustic simulation component can be simply replaced by a wave acoustic simulation (e.g., FDTD, FEM).

A ray tracing method [12] is used in this paper. The original ray tracing method assumes that incident waves are reflected specularly. Currently, however, scattering coefficients that emulate diffuse reflections [13] are used and implemented in commercial geometrical acoustic simulation software [14]. In this paper, the scattering coefficients are introduced such that the random reflection depends on the scattering coefficient and Lambert's law. The number of rays is 100,000 and ray tracking time is 5 seconds. The sampling frequency to calculate the echo time patterns is 20 kHz.

Figure 2 shows the shape and absorption coefficient of the hall that is analyzed in this study. The reverberation times obtained by using Sabine and Eyring's formulas are 1.85 [s] and 1.52 [s], respectively. The number of reflectors that are installed in the dotted area in the figure is $N \times N$ $(N = 1, 2, 3, 4)$. The reflector coordinates (x_c,y_c,z_c) are also shown in the figure. Setting the absorption coefficients of the reflectors to zero produces the theoretical reverberation time given above, which is independent of the number N. The scattering coefficients s of reflectors either set to zero (corresponding to no diffuse reflections) or are included as optimized variables (corresponding to diffuse reflections). The optimized variables are denoted by $\mathbf{r} = (\beta, \theta, s)$. The initial random values must lie within the definition area, such that β can assume values over the interval [0,50], θ assumes values over [0,1], and s assumes values over [0,1]. The PSO parameter γ is set to 0.6; this value is based on preliminary experiments that show that when γ is too large,

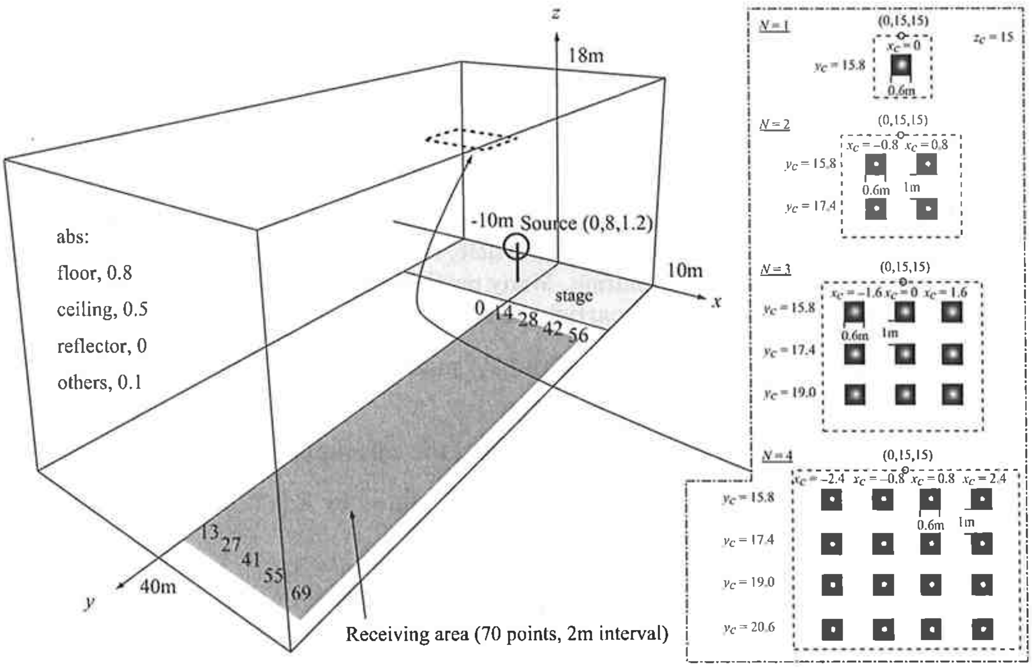


FIGURE 2: Geometry of the hall that is investigated in this study.

particles move out of the definition area, and when γ is too small, particles exhibit too little motion. The confidence on the particles and the swarm is equal (i.e., $c_1 = c_2 = 1$). The other parameters are $t = 1$ and $v_i^0 = 0$.

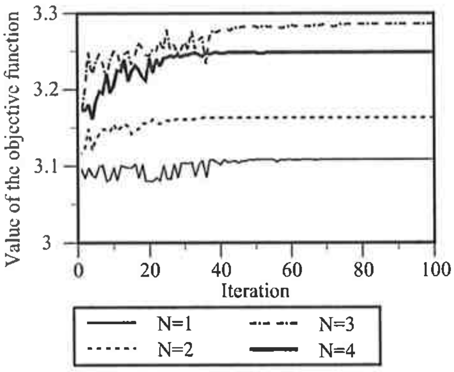
The receiving points are set at the rectangular grid in the figure. The coordinate for index m ($0 \leq m \leq 69$) corresponds to $(2 \times \mathrm{int}(m/14), 12 + 2 \times \mathrm{mod}(m, 14), 1.5)$, where int is a function that is floored to integer values, and $\mathrm{mod}(m, n)$ returns modulo when m is divided by n. There are eight cases in this experiment, corresponding to ($N = 1, 2, 3, 4$) with/without diffuse reflections. Starting from three different initial values to avoid local optima, 100 iterations are performed for the optimizations for the eight cases.

RESULTS AND DISCUSSION

Figures 3 and 4 show the maximum value of the objective function of the swarm, which corresponds to the maximum value among the three different initial states. Figure 3 is the case without diffuse reflections and Figure 4 is that with diffuse reflections. The objective function for these cases increases almost monotonically and converges in 100 iterations. For the case without diffuse reflection, the objective function at $N = 4$ is lower than that at $N = 3$. Thus, increasing the number of reflectors does not necessarily result in an increase in the value of the objective function.

Next, Figure 5 shows the initial variables on the β-θ plane for $N = 3$ without diffuse reflections. These results show that the variables are uniformly distributed over the plane. In contrast, Figure 6 shows the optimal variables after 100 iterations, where the asterisks correspond to the highest F values (i.e., the optimal value of the swarm). These results show that the particles are attracted to the optimal value of the swarm. The cases with diffuse reflections exhibit similar trends.

The variances of the acoustic indexes are compared at each receiving point for $N = 3$.



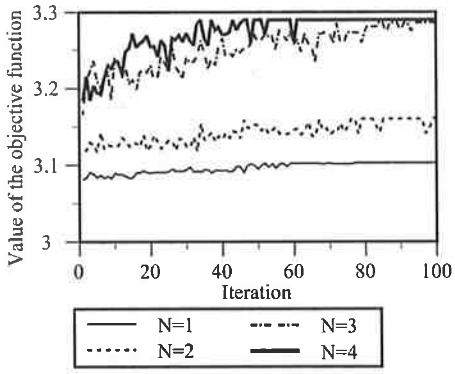


FIGURE 3: Change in the maximum value of the objective function F with the number of iterations. (without diffuse reflection)

FIGURE 4: Change in the maximum value of the objective function F with the number of iterations. (with diffuse reflection)

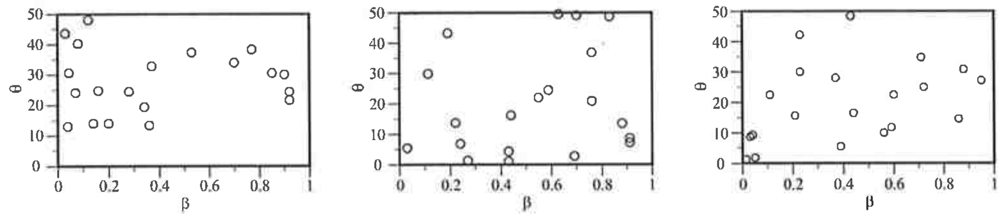


FIGURE 5: Initial values corresponding to three different initial states over the β-θ plane. (without diffuse reflections, $N = 3$).

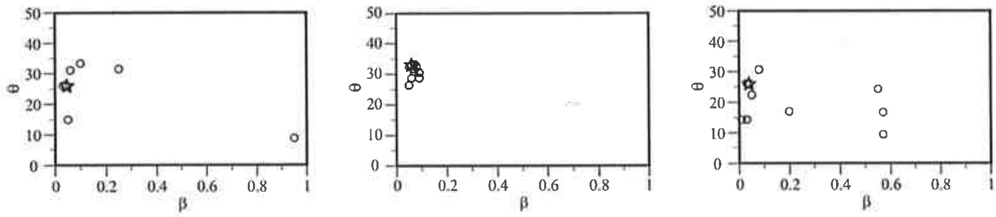


FIGURE 6: Values over the β-θ plane after 100 iterations on the initial values. The asterisks correspond to the optimal solution.

The variances after optimization should be smaller than the initial variances because the proposed method minimizes the variance of the indexes. Figure 7 shows the value of the C_{80} and T_{20} indexes, where the vertical lines in the figures show the nearest points from the stage in each raw. The results show that the variances decrease. The improvements in C_{80} in the center and the back side of the second row (ID 20-30) are especially significant. These results are caused by the reflectors delivering initial reflections that support direct sounds to the respective points. Although there is an insignificant change in T_{20} because the reflectors have no absorption, T_{20} decreases at some points by preventing echoes.

Figure 8 shows the optimized values of β and θ after 100 iterations. The results do not appear to be greatly affected by diffuse reflections. The $N = 2$ and $N = 4$ cases are similar in that the reflectors are not on the y axis ($x = 0$), whereas the $N = 1$ and $N = 3$ cases are similar in that the reflectors are on the y axis ($x = 0$). The $N = 2$ and $N = 4$ cases show smaller θ values, indicating that the reflector shape is almost a plate. The bent reflectors result in the incidence of direct sound on the ceiling with

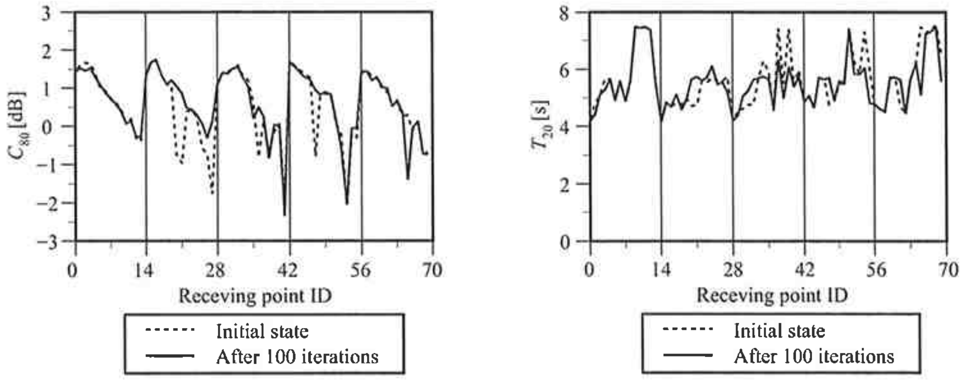


FIGURE 7: C_{80}[dB] and T_{20}[s] corresponding to the receiving points at the initial state and after optimization. (with diffuse reflections, $N = 3$).

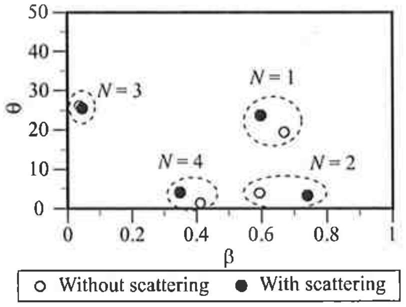


FIGURE 8: Optimal values over the β-θ plane after 100 iterations ($N = 1, 2, 3, 4$) without and with diffuse reflections.

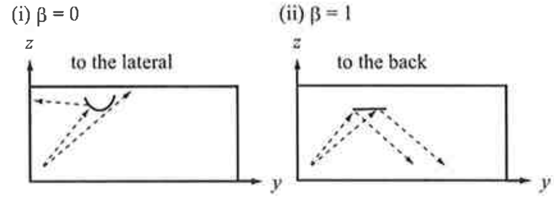


FIGURE 9: Schematics showing sound reflection at $\beta = 0$ and $\beta = 1$.

high absorption, such that sound clarity at the receiving points near the y axis decreases. Otherwise, the spaces between the reflectors are small and the F values increase. The $N = 1$ and $N = 3$ cases show comparatively larger θ-values. In these cases, the reflectors are always present on the y axis and the reflected sounds always return to the center, and then the increased bent in the reflectors results in the reflected sounds being transmitted to the lateral sections of the hall and correspondingly larger F value. A large or small β value translates to delivering the initial sounds to the lateral sections or the back of the hall, respectively. Figure 9 shows a section of the y-z plane for the same θ, with varying β. This result shows that sounds are delivered to the lateral sections of the hall for $N = 3$.

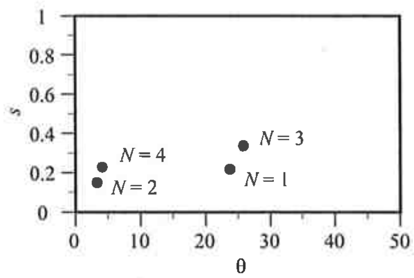


FIGURE 10: Optimal values on the θ-s plane after 100 iterations ($N = 1, 2, 3, 4$), without and with diffuse reflections.

Figure 10 shows the optimized distributions of θ and s with diffuse reflections. The scattering coefficients are between approximately 0.15 and 0.4. Excessively large scattering coefficients are undesirable.

Conclusions and Future work

In this paper, an optimal design method is studied to facilitate acoustical design by using numerical simulation instead of human experience. Optimized variables representing the properties of objects, and an objective function, which is related to the type of properties that are optimized, are designated and the method developed here can then optimize the variables automatically. An example of an acoustic reflector design is illustrated in this paper. The reflector properties are parameterized and an objective function is developed to minimize the variance of the room acoustic indexes. Thus, PSO can be used to obtain an optimal design. Future work will evaluate the effect of diffusers installed all over the room [9] or of the room shape in combination with a method to parameterize the room shape [15].

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