

Identification of a Set of Candidate Solutions for Optimal Positioning of Damping Layers

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ABSTRACT

One method to lower noise in a cabin is to position damping layers on vibrating panels, thereby reducing their radiated power. To assess the damping effect, criteria like the ERP (equivalent radiated power) are widely employed, which estimate the radiated sound power of a panel without taking into account the actual complex system.

Advantageously only a part of the structure has to be modeled, but the optimal solution found on the simplified model then often fails for the complete, coupled system, especially if several variants of a cabin have to be considered. Hence, it is proposed to use the structure-only optimization for identification of a set of candidate solutions for optimal positioning of damping layers. These candidate solutions used as initial designs for the coupled investigations should be well distributed in the design space to avoid being wrongly stuck in an optimum with inferior coupled performance.

Evolutionary optimization strategies are especially suited for such a multi-modal optimization to derive a candidate set of local optima. They perform better with a small number of design variables, which is achieved by a special parametrization approach for shape and position of damping layers suggested here. This enables the use of a multi-modal optimization method for the positioning of damping layers, which identifies not only one optimal position, but a set of good candidate solutions (set of local minima) on the coarse structure-only model, which are applied to several cabin variants and may be used as initialization and acceleration of coupled optimization.

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INTRODUCTION

In the automotive design process, one important goal is to obtain a very low level of noise inside the cabin, for the car to make a comfortable and high-quality impression. An effective way to decrease interior noise is to reduce the structure borne noise by application of damping layers to vibrating panels. Packaging requirements have to be considered, usually prescribing a maximum thickness of damping layers. Furthermore, adding damping layers adds additional mass to the system, which is unwanted in automotive design. Therefore, research in the field of numerical optimization to obtain optimum characteristics of viscoelastic damping layers started as early as 1998 with the work by Lumsdaine and Scott [1], who considered the thickness of volume elements in a finite element simulation as design variables. An overview of the history of structural-acoustic optimization is given in [2]. Regarding position and shape optimization of damping layers, or similar layout optimization of materials to reduce the radiated power of a structure, the most widely used method is topology optimization, as seen in for example [3; 4; 5; 6; 7]. Our work differs from these, as not only one optimum is sought, but a set of optimal solutions. For that, it is necessary to use multi-modal optimization algorithms, for which evolutionary algorithms are especially suited. Although evolutionary

or genetic algorithms have been used before, the reason for that was mostly the use of a black box finite element simulation as objective function [8]. In [9] different optimization methods along with a morphing parametrization are compared.

Obviously, noise reduction means should be considered as early as possible for design, but this poses a problem, as there always is a lack of knowledge during those early design phases. This is of course true for all design objectives, but interior noise characteristics are especially sensitive to the exact configuration of the interior of the cabin, which is not known until very late in the design process.

Therefore, it has been of interest for a long time to employ auxiliary goals, for instance by regarding only a structural domain, which makes it possible to evaluate the potential noise caused by the structure early on. In addition, as usually a high amount of simulations are necessary for optimization, the faster computation times caused by considering only the structure are highly desirable. Structural objective functions, for example the mean level of structure borne sound (MLS) or the equivalent radiated power (ERP), have been used for instance in the work of [8]. A comparison of different methods to evaluate the radiated sound power of a structure

is conducted in [10]. An alternative to using structure-only models with estimations of radiated sound power is the creation of a reduced order model for the coupled structure-fluid system, as used in [11], for which again full knowledge of the system is required. Here, we propose to use structure-only optimization first, and in a later step to switch to a model of the coupled system, which is similar to the workflow shown in [12], but differs by employing multimodal optimization.

In this work, the ERP is considered as the objective function of the structure-only part of the optimization. Based on results of a finite element simulation, it is computed by summing up the squared normal nodal velocities v_n weighted by element sizes. The simulation runs in frequency space, which means that at frequency ω , the acceleration can also be described in terms of nodal displacements as $v_n^2 = \omega^2 |u_n(\omega)|^2$. Under the simplifying assumption of a radiation efficiency $\sigma = 1$, the pressure of the adjacent acoustic fluid is related to the structural velocities by the acoustic base impedance $Z_0 = \rho_0 c_0$, with density ρ and sound velocity c . Considering a structure with area S , the ERP can be expressed as

$$\text{ERP}(\omega) = Z_0 \omega^2 \int_S |u_n(\omega)|^2 ds. \quad (1)$$

A detailed derivation of the ERP as well as extensive explanations are found in the textbook by Kollmann [13].

So what is the point of doing a multi-modal optimization in the structure-only part of the optimization method? One of the drawbacks of using a simplified structure-only model is the fact that optimization results may not capture the behavior of the complex model. Although the results are very robust in the sense that they are not influenced by fluid characteristics and not yet known cabin specifications at all, they tend to be imprecise and, in the worst case, also lead to configurations that trigger unwanted effects in the fluid, and thereby might even amplify cabin noise. This can be countered by finding not one global optimum of the simplified model, but search for a set of good candidate solutions. Those candidate solutions are local optima of the simplified optimization problem, which should be clearly distinguishable from each other and well distributed in the design space. Starting the treatment of the complex model with a set of solutions instead of just one makes it possible to then discard designs that do not work well with the full model, without having to re-iterate the structure-only optimization.

The considered structure of the coarse model is a part of the fine model, which may be re-used in different variants of the complex cabin model. This means that one run of the simplified model multi-modal optimization creates potential solutions for a variety of variable complex models.

This method is only valid in a multi-modal design space, that is a design space including different minima, but it is shown later that the problems treated here fall in that category. If the multi-modal optimization is being run with an uni-modal objective function, it nevertheless still identifies its single minimum, but not a set of good

candidates, in fact working as a slower global optimization. It requires some engineering knowledge to decide beforehand if using multi-modal optimization is applicable to a specific use case.

OPTIMIZATION WORKFLOW

The optimization method proposed in this paper consists of three hierarchical main steps, namely multi-modal position optimization, uni-modal shape optimization and evaluation on the fine model level, see Fig. 1, which are explained in the following sections. It is important to note that the shape and position optimization, which require a large number of function evaluations, are performed on the computationally fast structure-only model, and only the last step requires a complex fluid-structure model. Furthermore, by finding a set of candidate solutions, it is usually not necessary to iterate back over the simple model, which means the shape and position optimization can be done in advance, so there is not much computational time and effort required to adapt those solutions once the full model is known.

Multi-Modal Position Optimization

For the multi-modal position optimization, an algorithm called Crowding Differential Evolution (Crowding DE) is used, which was first introduced by Thomsen in 2004 [14]. It is based on the Differential Evolution (DE) algorithm created by Price and Storm in the 1990s [15]. For more general information about the topic of multi-modal optimization, the reader is referred to the textbook by Preuss [16], detailed information about the differential evolution algorithm are found in, for example, the textbook by Feoktistov [17].

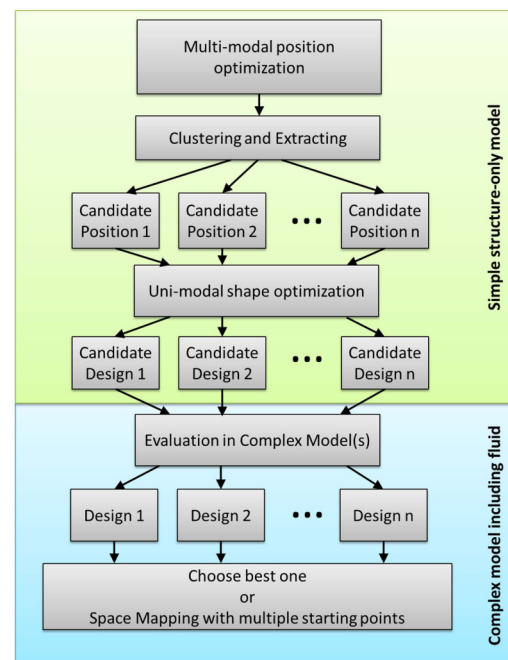


Figure 1. Overview of the Optimization Method

The Crowding DE algorithm, applied to the positioning of a damping layer of fixed shape, size and thickness, is shown in Fig. 2. The only step of the Crowding DE which differs from conventional DE is the selection step, which is further accentuated in Fig. 2.

The principal idea behind differential evolution is the comparison of an individual to a trial vector. This trial vector is created by combining an individual from the current population with differences between further individuals. If the trial vector turns out to be better in terms of the considered objective, it replaces the original individual. In classical DE, this process is repeated in each generation until every individual in the population has been tested. This constitutes a global optimization algorithm.

In multi-modal optimization, it is not desired that all individuals converge to the global optimum. Instead, local optima are required to be conserved. This is accomplished by changing the selection step to always have the trial vector challenge the most similar individual, which makes it impossible for a group of designs in the vicinity of a local optimum to jump to a better one, since they are always tested against individuals from their group. Of course, a measure of similarity has to be defined for this, which can be quite difficult for arbitrary, high dimensional design spaces. But in the case considered here, that is the positioning on a two-dimensional plane, Euclidean distance is available to characterize similarity. Although by challenging the closest individual, it is not guaranteed anymore that every individual is tested in one generation, and a single individual may be tried and even replaced more than once, the term generation is kept for an amount of iterations equal to the number of individuals in the population. This also means that convergence can be expected to be slower compared to the uni-modal case, because badly positioned individuals might stay in the population for some generations without being tested.

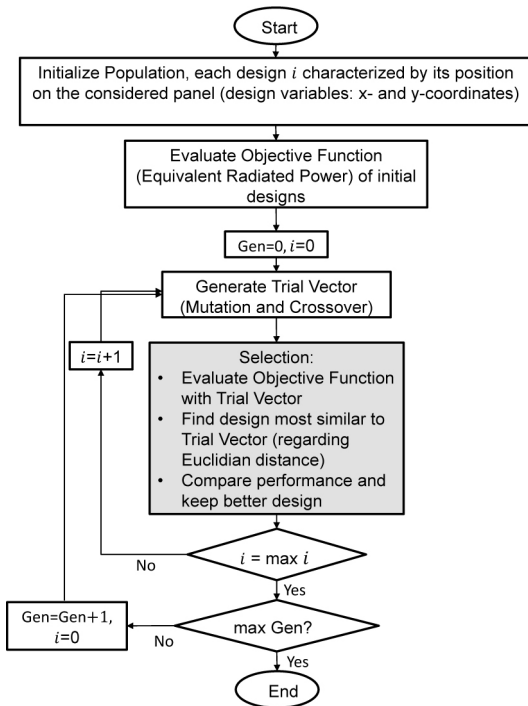


Figure 2. Multi-modal position optimization of a damping layer on a vibrating panel, regarding ERP as objective function, Crowding Differential Evolution as optimization algorithm.

The result of a multi-modal optimization is a number of subsets of designs, where each group is converging to a local minimum. In post-processing of the optimization, these groups or clusters have to

be identified, which is done in this work by using the algorithm DBSCAN proposed in [18], in which clusters are found through their property of having a higher density than the surroundings. This algorithm only needs two input parameters, namely a characteristic distance and the minimum number of points to form a cluster.

Uni-Modal Shape Optimization

Following the multi-modal position optimization, a number of promising designs from the set of local optima are chosen for further shape optimization. In this work, both optimizations are performed on the structure-only model with respect to a minimum ERP.

An advanced parametrization is used, based on a method developed in the field of computer graphics, more precisely 2D-animations. A nonlinear least-squares optimization is employed for deformation of an initial shape into a known final shape [19]. In contrast, here no known final shape exists, but randomly chosen vertices are displaced in an outer optimization loop, and the rest of the shape is following intuitively according to the criteria explained below. Thereby the number of design variables, and of possible infeasible shapes is reduced greatly, compared to a shape optimization where all vertex coordinates are direct design variables.

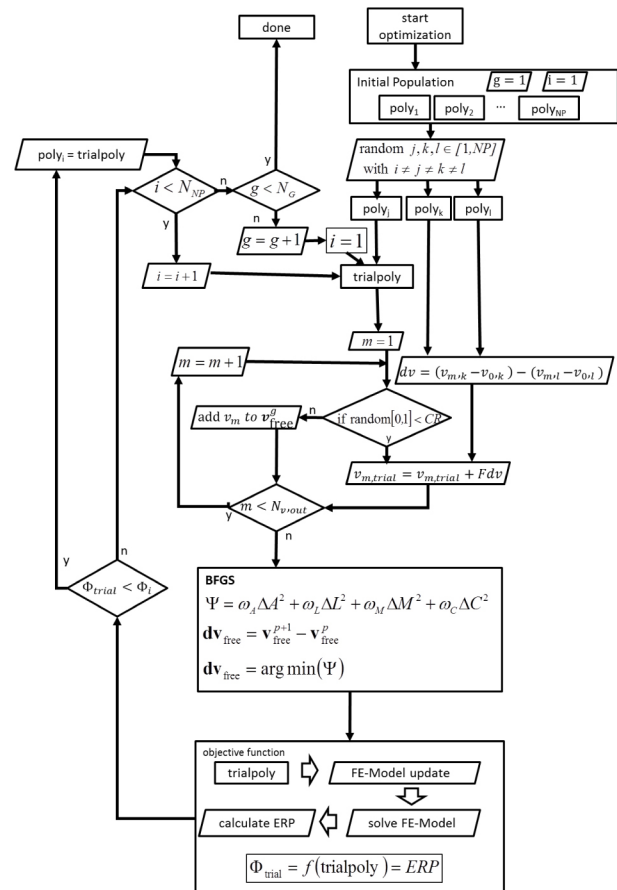


Figure 3. Overview of the Optimization Method

The shape of the damping layer is described by a mesh forming a polygon with vertices v_i and edges e_i . An exemplary mesh is shown in Fig. 4. This mesh is created exclusively for shape optimization and is not used as the finite element mesh in function evaluations. By using