Matthias Ehrgott Carlos M. Fonseca
Xavier Gandibleux Jin-Kao Hao
Marc Sevaux (Eds.)

Evolutionary Multi-Criterion Optimization

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Matthias Ehrgott
The University of Auckland, Department of Engineering Science
70 Symonds Street, Room 415, Auckland 1001, New Zealand
E-mail: m.ehrgott@auckland.ac.nz

Carlos M. Fonseca
Universidade do Algarve, Faculty of Science and Technology
Department of Electronic Engineering and Informatics
Campus de Gambelas, 8005-139 Faro, Portugal
E-mail: cmfonsec@ualg.pt

Xavier Gandibleux
Université de Nantes, Faculty of Sciences and Technology
Laboratoire d' Informatique de Nantes-Atlantique, UMR CNRS 6241
2, Rue de la Houssinière, BP 92208, 44322 Nantes Cedex 03, France
E-mail: Xavier.Gandibleux@univ-nantes.fr

Jin-Kao Hao
Université d'Angers, LERIA, Faculty of Sciences
2 Boulevard Lavoisier, 49045, Angers Cedex 01, France
E-mail: Jin-Kao.Hao@univ-angers.fr

Marc Sevaux
Université de Bretagne-Sud - UEB, Lab-STICC - UMR CNRS 3192
Centre de Recherche BP 92116, 56321 Lorient Cedex, France
E-mail: marc.sevaux@univ-ubs.fr

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Robust Design of Noise Attenuation Barriers with Evolutionary Multiobjective Algorithms and the Boundary Element Method

David Greiner, Blas Galván, Juan J. Aznárez, Orlando Maeso, and Gabriel Winter

Institute of Intelligent Systems and Numerical Applications in Engineering (SIANI), 35017, University of Las Palmas de Gran Canaria, Spain
{dgreiner,jaznarez,omaeso}@iusiani.ulpgc.es,
{bgalvan,gabw}@step.es

Abstract. Multiobjective shape design of acoustic attenuation barriers is handled using a boundary element method modeling and evolutionary algorithms. Noise barriers are widely used for environmental protection near population nucleus in order to reduce the noise impact. The minimization of the acoustic pressure and the minimization of the cost of the barrier -considering its total length- are taken into account. First, a single receiver point is considered; then the case of multiple receiver locations is introduced, searching for a single robust shape design where the acoustic attenuation is minimized simultaneously in different locations using probabilistic dominance relation. The case of Y-shaped barriers with upper absorbing surface is presented here. Results include a comparative between the strategy of introducing a single objective optimum in the initial multiobjective population (seeded approach) and the standard approach. The methodology is capable to provide improved robust noise barrier designs successfully.

Keywords: Engineering Design, Evolutionary Multiobjective Optimization, Noise Barriers, Acoustic Attenuation, Uncertainty, Computational Acoustics.

1 Introduction

Shape optimization has been performed in recent years applied to various fields of computational mechanics, such as aeronautics or solid mechanics using evolutionary algorithms [4,5]. Automatically generated optimum designs are possible by using coupled evolutionary computation with accurate numerical modeling.

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The paper describes in the second section the acoustic attenuation modeling using BEM, following with the Y-shaped noise barrier optimum design methodology and

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1 Introduction

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The paper describes in the second section the acoustic attenuation modeling using BEM, following with the Y-shaped noise barrier optimum design methodology and problem description, test case, results and discussion. Finally it ends with the conclusions and references.

2 Noise Barriers Acoustic Attenuation Modelling

Sound propagation calculation can be performed efficiently and successfully with the Boundary Element Method (BEM). The main advantages of BEM [9] over other methods based on a geometrical theory of diffraction approach are its flexibility (arbitrary shapes and surface acoustic properties can be accurately represented) and accuracy (a correct solution of the governing equations of acoustics to any required accuracy can be produced providing a boundary element size with small enough fraction of a wavelength). Nowadays, both BEM and the Finite Element Method are the most extended state of the art discretization methods in the computational acoustics field [26]. Concretely, to estimate the efficiency of noise barriers with complex shapes, the BEM has been used from the 80s [6,17,23] and it is still a field of research interest. In recent years, design of noise barriers has been taken into account using BEM, see e.g. [24].

The integral equation for a boundary point *i*, to be solved numerically by BEM, can be written as:

$$c_i\, p_i = p_o^* - \int_{\Gamma_b} \left(\frac{\partial p^*}{\partial n} + \mathbf{i}\, k\, \beta_b\, p^* \right) p \, d\Gamma \qquad \textbf{(1)}$$

where:
p: acoustic pressure field on the barrier surface (Γ_b) of generic admittance β_b.
p^*: half-space fundamental solution. Acoustic pressure field due to a source at collocation point i over a plane with admittance β_g (ground surface). This fundamental solution only requires the discretization of the barrier boundary (Γ_b). For perfectly reflecting surfaces (barrier or ground), $\beta=0$. If the surface is absorbent, the evaluation of β is obtained from the complex admittance of Delany and Bazley [8] knowing the covering material thickness and its air flow resistivity.
c_i: the local free term at collocation point i: $c_i = \theta / 2\pi$, where θ is the angle subtended by the tangents to the boundary at this point (rads). c_i =0.5 for smooth boundaries.
p_o^*: half-space fundamental solution at problem source due to collocation at point i.
$k = \omega/c$ is the wave number (c: sound wave velocity, ω: angular frequency) and **i** the imaginary unit.

The numerical solution of Eq. 1 is possible after a discretization process. A linear system of equations is obtained from this process and lead to values of acoustic pressure over the barrier boundary. The BEM code in this paper uses quadratic elements with three nodal points. For more details about the used model, see [21][22].

3 Y-Noise Barriers Shape Design Optimization

In recent years, noise barrier optimum design has been solved using evolutionary computation. Some works related with single objective optimization are [1,3,10,14].

The simultaneous minimization of two conflicting objectives corresponding to a noise barrier design is performed in this paper. First, a fitness function related with the increase of the acoustic attenuation of the barrier. Concretely, the first fitness function which has to be minimized is:

$$F1 = \sum_{j}^{NFreq} \left(IL_j - IL_j^R \right)^2 \tag{2}$$

where:

IL_i : insertion loss in the third octave band centre frequency for the Y-barrier profile evaluated. Being the *insertion loss* (*IL*), defined as stated in Equation 3 (being dBA the units of IL):

$$IL = -20 \log \left(\frac{P_S}{P_B} \right) dBA \tag{3}$$

and calculated at one-third octave band spectra, where P_B and P_S are the acoustic pressure at the receiver with and without the presence of the barrier respectively. This parameter is an accepted estimation of the acoustic efficiency of the analyzed profile.

IL_i^R: insertion loss reference curve in the third octave band centre frequency. When choosing a reference with high IL values, a high efficient attenuation barrier fitting is searched.

The optimum monocriteria design using this first fitness function was previously described in Greiner et al. [14]. It solves an inverse problem, where the objective IL curve at certain frequencies is known (IL^R) and it allows to search for the corresponding barrier design whose IL curve fits IL^R. In [14] was shown the capability to increase a certain percentage the acoustic efficiency of a certain Y-shape barrier taken as original design.

The second fitness function (F2) to be minimized is the noise barrier length, representative of the raw material cost. The higher its value, the easier the noise attenuation capacity of the barrier, and therefore, the easier to fit the searched reference curve. On the contrary, the lower its value, the lower the cost and better environmental impact produced by the barrier.

Here, a multiobjective optimization noise barrier design with evolutionary algorithms is introduced. Concretely, the procedure searches for the barrier shape design which most fits IL^R for each barrier length value.

The modelling approach included in the paper follows the test case implementation of the previous related referenced works and is intentionally chosen because of the simultaneous capability to cover the design space and also to reduce the number of variables of the search optimization (could be interpreted as helping the search including engineering knowledge). The Y-barrier shape is modeled using the two extreme points of the arms and their join point. The x coordinate of the extreme points is supposed fixed in the extremes of the barrier, where only y-coordinate varies. The join point has variable x- and y-coordinates. The evolutionary algorithm variables are set in a transformed space with perpendicular axis and square shape in contrast to the geometric trapezoidal shape limited by b and the sloped line (see Fig. 1). So, four design variables are required to define each shape (the x coordinate vary from -0.5 to +0.5 and the three y coordinates vary from 0 to 1 in the transformed space). For more details, see [14].

With this geometry and for a given source position, the boundary element program calculates the acoustic pressure at the receiver position (r). A maximum element length not bigger than λ / 4 (being λ the wavelength) is necessary to obtain an appropriate accurate solution. With the acoustic pressure, the IL corresponding to each frequency is obtained.

In case we want to consider not a single receiver location, but a certain zone where to minimize the acoustical impact, then various receiver locations are needed and a robust design is pretended, considering the minimization of function F1 at each receiver. Therefore we deal not with a single value, but with a set of F1 values (a distribution estimation). Uncertainty handling in evolutionary optimization has been covered in recent years as a growing field of interest, see e.g. [2, 11, 19]. We follow here the proposal of Teich [25], including the probabilistic dominance relation in the NSGA-II as shown in [20]. So, the F1 objective is not a number, but a random variable with values bounded by an interval evaluated as the average of the F1 values at the receiver points plus and minus their typical deviation.

4 Test Case

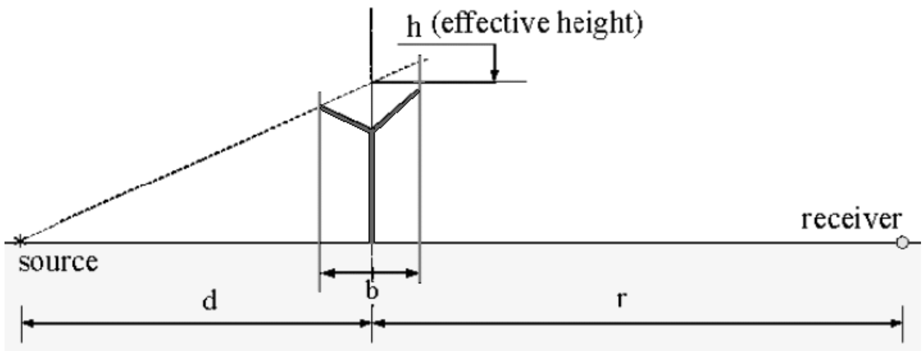

Fig. 1. Problem topology representation.

The parameters considered in the test case used in the following experiments are according to Fig. 1: b=1m. and d=10m. (noise source distance to the barrier base) We will compare the single-point and multi-point receiver cases. In case of a single receiver, r= 50m. In case of multiple receivers, three receiver positions are taken into account (r=25, 50 and 100m., respectively). The ILref curve is obtained from a straight barrier of 4.5 m height with reflecting surfaces, versus the maximum effective height allowed of our Y-shaped designs of 3.0 m. We will consider only reflecting surfaces, with the exception of the upper boundary of the design (inner surfaces of the arms), which are absorbing surfaces. A thickness of 10 cm and an air flow resistivity of 20000 are considered for the calculations described in section 2. A total of 13 frequencies at one-third octave centre band spectra frequency are evaluated: 100, 125, 160, 200, 250, 315, 400, 500, 630, 800, 1000, 1250 and 1600 Hz. The CPU time cost of one F1 fitness function evaluation is 12 seconds in one Pentium IV-3GHz processor.

5 Results and Discussion

Twelve independent runs of the evolutionary optimization design were executed in each case. A population size of 100 individuals and 3% mutation rate were used in a Gray coded [27] NSGA-II algorithm with uniform crossover and probabilistic dominance relation (α=0.5).

Two cases are analyzed: 1. The single point receiver case. 2. The multi-point receiver case. Each one has been solved comparing two different initial population strategies: a) A seeded approach, where a solution of high quality is inserted into the initial population; e.g., see [15]. b) The standard no-seeded initial random population approach.

5.1 About the initial Population Strategy

The inserted high-quality design is obtained performing a single-objective steady-state evolutionary algorithm optimization on F1. Each of the twelve independent runs obtained the same final value, which will be considered as the optimum in terms of F1. The number of evaluations required to reach the optimum for each run is shown in Table 1. The average values in obtaining the optimum for the single-point and multi-point receiver cases are 4346 and 4526 function evaluations. Since the average values computed are principally influenced by the greatest values of Table 1, if we delete the best and worst values, avoiding the excessive influence of extremes, then the average values are 4005 and 3053, respectively; showing in average that the multi-point receiver case needs less function evaluations.

Table 1. Number of evaluations required to reach the optimum value in the single objective optimization (F1) and average (in italic type)

Single-Point Receiver	3786	6050	3806	4164	2020	3212	*Average*
	4706	2904	10080	4240	3758	3428	*4346*
Multi-Point Receiver	2826	4606	3044	21844	2970	2344	*Average*
	2044	3790	2392	1934	3760	2758	*4526*

In contrast, the best values in terms of F1 obtained after 45000 fitness function evaluations with the multiobjective no-seeded search are shown in Table 3: Only one out of 24 runs were capable to achieve this F1 best solution design.

To compare the outcome of the whole front, we will evaluate the S-metric (hypervolume, originally proposed by Zitzler [28]) of various attainment surfaces.

Concretely, we use the S-metric proposal of Fonseca et al. [12][1]. The attainment surface concept in multiobjective optimization was introduced in [13,16] and we use here the approach suggested in Knowles [18][2].

Table 2. S-Metric (Hypervolume) Results, with Reference Point (2000, 9), including the attainment surfaces 1, 3, 5 and 7 over 12. The constrained space results consider only solutions with F2 values greater than 3.6 m.

	S Metric (Unconstrained Space)		S Metric (Constrained Space)	
Initial Population Strategy – Number of Evaluations	Single Point Receiver	Multi Point Receiver	Single Point Receiver	Multi Point Receiver
	Attainment Surface 1	Attainment Surface 1	Attainment Surface 1	Attainment Surface 1
Noseed - 15000	14420.7833	14412.6969	10790.7287	10789.0082
Noseed - 30000	14425.8523	14421.1657	10790.9215	10789.1444
Noseed - 45000	**14428.0118**	**14423.7072**	10790.3783	**10790.4215**
Seed - 10000	14407.9250	14406.2951	10791.8617	10788.3595
Seed - 25000	14417.2164	14420.7298	10792.5499	10788.7074
Seed - 40000	14420.7381	14423.1665	**10792.6384**	10788.7788
	Attainment Surface 3	Attainment Surface 3	Attainment Surface 3	Attainment Surface 3
Noseed - 15000	14394.8957	14392.7734	10790.3061	10788.6518
Noseed - 30000	14402.1018	14397.0153	10790.6493	10788.9019
Noseed - 45000	**14407.4146**	14400.8746	10790.2065	**10790.2490**
Seed - 10000	14390.6412	14385.8869	10791.4474	10788.0735
Seed - 25000	14398.1735	14396.3221	10792.2399	10788.4565
Seed - 40000	14400.7514	**14401.7005**	**10792.4660**	10788.6195
	Attainment Surface 5	Attainment Surface 5	Attainment Surface 5	Attainment Surface 5
Noseed - 15000	14382.4308	14381.0581	10789.5308	10788.2375
Noseed - 30000	14387.7540	14385.4327	10790.4415	10788.7214
Noseed - 45000	**14391.4587**	**14387.9532**	10790.0582	**10790.0954**
Seed - 10000	14379.4652	14373.8816	10790.7003	10787.8379
Seed - 25000	14386.4227	14382.8896	10792.0495	10788.2732
Seed - 40000	14388.7318	14386.0760	**10792.2480**	10788.4440
	Attainment Surface 7	Attainment Surface 7	Attainment Surface 7	Attainment Surface 7
Noseed - 15000	14371.1840	14370.0224	10788.7894	10787.9192
Noseed - 30000	14376.9554	14375.0176	10790.2124	10788.5177
Noseed - 45000	**14379.5126**	**14376.3961**	10789.8960	**10789.8911**
Seed - 10000	14368.6691	14362.9460	10790.4835	10787.4946
Seed - 25000	14374.9322	14372.3565	10791.9008	10788.0779
Seed - 40000	14378.1628	14374.9925	**10792.0855**	10788.2863

[1] Source code available at: http://sbe.napier.ac.uk/~manuel/hypervolume

[2] Source code available at: http://dbkgroup.org/knowles/plot_attainments

We will consider four attainment surfaces, 1 (100%), 3 (83%), 5 (67%) and 7 (50%) out of 12 (total number of independent runs per case), and evaluate its hypervolume after 15000, 30000 and 45000 fitness evaluations in case of no-seeded strategy and 10000, 25000 and 40000 fitness evaluations in case of seeded strategy (a fair comparison to take into account the cost of the included solution). As reference point in S-metric calculation, a point sufficiently high has been selected, whose coordinate values of F1 and F2 are respectively, 2000 and 9. In the multi-point receiver case, the average of F1 has been considered for hypervolume calculation. Results are shown in table 2. In this problem the decision maker region of interest is located in the left part of the search space (low F1 values and high barrier length, being the higher F1 values not useful). So, we have also evaluated the S-metric in a constrained design space over a barrier length greater than 3.6 meters. The important information of Table 2 has been put in bold style.

Table 3. Values of the best F1 solutions achieved each run in the standard no-seeded population strategy

	Single Point Receiver		Multi Point Receiver	
	Best F1 value	Corresponding F2 value	Best F1 value	Corresponding F2 value
Run Number 1	0.793816	5.11963	1.01041	5.16681
Run Number 2	0.789535	5.12731	0.99224	5.14777
Run Number 3	0.792179	5.13680	0.993157	5.15853
Run Number 4	0.792731	5.13644	0.99390	5.15735
Run Number 5	0.815023	5.16626	0.991989	5.14819
Run Number 6	0.830437	5.13460	1.00177	5.15647
Run Number 7	0.963581	5.18668	1.00676	5.17805
Run Number 8	0.796091	5.15574	1.00847	5.17743
Run Number 9	0.787557	5.11747	1.01499	5.15646
Run Number 10	0.796999	5.16681	0.994803	5.13744
Run Number 11	0.792993	5.09903	0.994803	5.13744
Run Number 12	0.794859	5.14713	1.00739	5.11768
Best Value	0.787557	5.11747	0.991989	5.14819
Seeded Value	0.787300	5.11796	0.991989	5.14819

Considering the unconstrained space S-metric results, in all cases minus one (3rd attainment surface of multi-point receiver case at 40000 evaluations: 14400.8746 < 14401.7005), the no-seeded strategy achieves a better (higher) hypervolume. The introduced bias towards the optimum may be detrimental to the evolution. In the constrained space, there are manifested two opposite behaviors: in case of the single-point receiver runs, the seeded approach is better in all circumstances over the no-seeded strategy; but in the multi-point receiver case, the no-seeded approach is better in all circumstances over the seeded strategy. That is an indicator of how this multi-point receiver problem has a different landscape than the single-point receiver one.

5.2 Single-point versus Multi-point Receiver Cases

The accumulated optimum non-dominated solutions are represented in Figures 2 and 3 in search space, showing independently the single-point (crosses) and multi-point (circles) receiver cases. We have focused on the left functional search space part, because it is the region of interest for the designer. In this multi-point receiver problem, only the average of F1 is plotted for clarity.

Seven designs (1 to 7 in the single-receiver and 1' to 7' in the case of the multi-receiver) have been chosen along the decision-maker region of interest. They have been marked in the non-dominated front in Figure 3 and their shape designs are represented in Figure 4 (single-receiver) and Figure 5 (multi-receiver). The numerical values of their fitness functions and design variables are shown in Table 4 (single-receiver) and Table 5 (multi-receiver). The single-point receiver front dominates the multi-point receiver front, as can be seen in Figure 3. The need of a robust behaviour when considering various receiver locations implies higher average values of the fitting of the ILref curve. In Table 6 the values of F1 corresponding to the three receiver points are represented for the fourteen designs. In Table 6, we observe in detail the best F1 solutions of both approaches: Design 1 (D1) and Design 1' (D1'). D1 has the best F1 value in receiver point 2 (distance to the barrier base = 50m.), but an F1 average of 1.036, which is worse than the best value of D1' (0.991989). By the other hand, the value of F1 at receiver 2 of D1' is worse (0.847302 > 0.78730) than the value of D1.

In Figure 6 both the Reference IL curve (corresponding to a 4.5 straight barrier with reflecting surfaces) and the best fitted solutions D1 and D1' are represented for each receiver point. In the x axis the third octave centre spectra frequency is represented in Hertz in logarithmic scale. In the y axis the IL is represented in dbA units. As can be seen in the figures, the obtained designs fit accurately the searched IL reference curve, and their differences are really low. Therefore, that means that the same acoustic attenuation efficiency of a 4.5 meters effective height straight barrier can be achieved with a 3.0 meters effective height Y-shaped barrier with absorbent treatment in the inner surface of its arms. The multiobjective approach allows also to locate for each barrier length the barrier that fits most precisely the former noise attenuation capability (the lower the length, the worse the IL curve fit).

Table 4. Fitness functions and transformed coordinates values corresponding to the seven selected optimum designs of the single-point receiver case.

SinglePoint Receiver Design	F1	F2	y-Coord1	x-Coord2	y-Coord2	y-Coord3
Design 1	0.7873	5.11796	0.972549	-0.04902	0.262745	1.0000
Design 2	1.37468	4.93885	0.976471	0.013725	0.333333	1.0000
Design 3	1.8395	4.71724	0.976471	0.045098	0.419608	1.0000
Design 4	1.89081	4.09768	0.988235	-0.272549	0.737255	1.0000
Design 5	2.551	3.95284	0.952941	-0.296078	0.733333	0.964706
Design 6	5.24347	3.85126	0.94902	-0.272549	0.745098	0.937255
Design 7	7.25369	3.73438	0.917647	-0.194118	0.72549	0.917647

Table 5. Fitness functions and transformed coordinates values corresponding to the seven selected optimum designs of the multi-point receiver case.

MultiPoint Receiver Design	F1 Average	F2	y-Coord1	x-Coord2	y-Coord2	y-Coord3
Design 1'	0.991989	5.14819	0.968627	-0.041176	0.247059	1.0000
Design 2'	1.88108	4.87903	0.976471	0.288235	0.380392	1.0000
Design 3'	2.54528	4.63693	0.968627	0.02549	0.439216	0.996078
Design 4'	2.60501	4.01638	0.952941	-0.272549	0.701961	0.972549
Design 5'	3.15836	3.94612	0.941176	-0.268627	0.717647	0.968627
Design 6'	5.99898	3.85323	0.94902	-0.3.0000	0.74902	0.933333
Design 7'	7.57026	3.7397	0.909804	-0.217647	0.721569	0.921569

Table 6. Fitness function F1 value at each receiver of the seven selected designs, average and variance corresponding to both the single and multi-point receiver case. (It is hignlighted in italic type the value used as search criterion in the optimization process)

i: SinglePoint Rcptor Design i': MultiPoint Rcptor Design	F1 at Receiver 1	F1 at Receiver 2	F1 at Receiver 3	F1 Average	F1 Variance
Design 1	1.061216	*0.787300*	1.260585	1.036367	0.037642
Design 2	1.909043	*1.374685*	1.919018	1.734248	0.064660
Design 3	2.163635	*1.839499*	2.304096	2.102410	0.037849
Design 4	3.725551	*1.890806*	2.313488	2.643282	0.615430
Design 5	5.594426	*2.550998*	3.511254	3.885559	1.613795
Design 6	7.447395	*5.243466*	5.302573	5.997811	1.051228
Design 7	7.952338	*7.253690*	8.081641	7.762557	0.132259
Design 1'	0.748688	0.847302	1.379976	*0.991989*	*0.076888*
Design 2'	2.074511	1.624732	1.943987	*1.881077*	*0.035696*
Design 3'	2.148006	2.402341	3.085492	*2.545280*	*0.156696*
Design 4'	3.007588	1.899501	2.907952	*2.605014*	*0.250528*
Design 5'	2.731014	2.577981	4.166087	*3.158361*	*0.511659*
Design 6'	7.334568	5.286570	5.375808	*5.998982*	*0.893222*
Design 7'	6.832536	7.135412	8.742823	*7.570257*	*0.702745*

6 Conclusions

Concerning the problem of multiobjective optimum design of noise barriers, a methodology for considering various receiver points has been introduced in this paper successfully, allowing to obtain robust optimum shape designs that fit various IL reference curves (each receiver represent a IL reference) simultaneously.

Related to the initial population strategy, it has been shown that in certain cases (here the single-point receiver case) the seeded approach introducing one high quality solution design into the initial population, can be useful to obtain improved final fronts. Nevertheless, the reasons that justify when this strategy is profitable or not, should be further investigated.

Taking into account the obtained results in terms of qualitative design information, it is remarkable that introducing the robust design methodology does not lead to new shape designs, being only slight variations of coordinates along the non-dominated front respect the single-point receiver optimization designs.

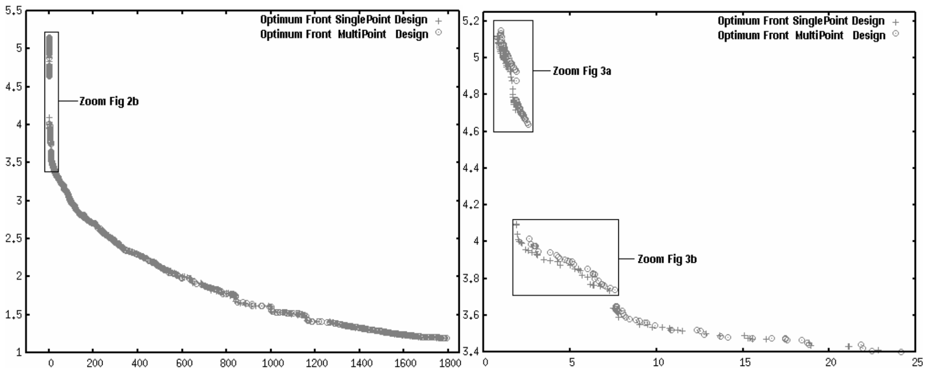

Fig. 2. Non-Dominated final accumulated optimum front function evaluations, including both single-point (crosses) and multi-point (circles) receiver cases. The total front (2a, left) and zoomed left portion (2b, right) are shown. F1 in x-axis and F2 in y-axis

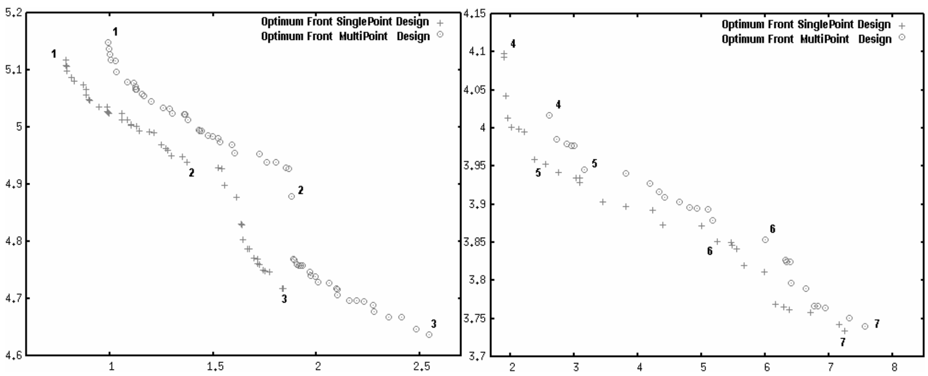

Fig. 3. Zoomed portions (3a, left) and (3b, right) of the non-dominated final accumulated optimum front function evaluations, including the numbering of seven selected designs for both single-point (crosses) and multi-point (circles) receiver cases. F1 in x-axis and F2 in y-axis

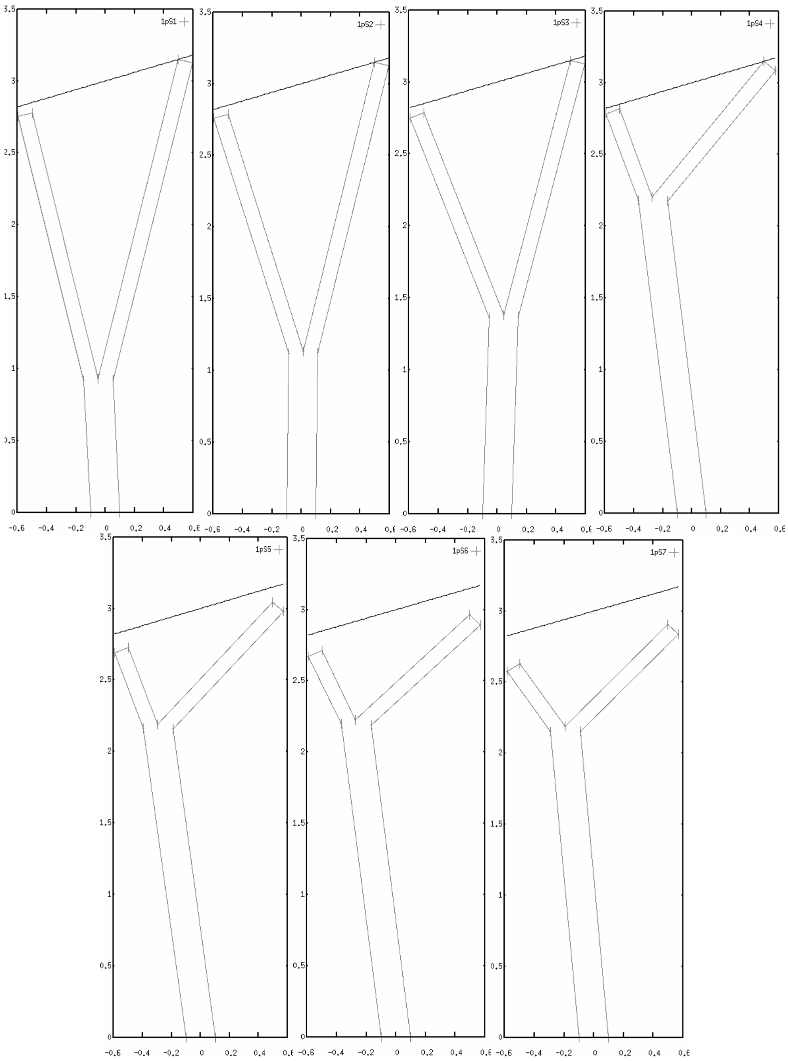

Fig. 4. Shapes of the 7 selected designs, from 1 (left) to 7 (right), single-point receiver case.

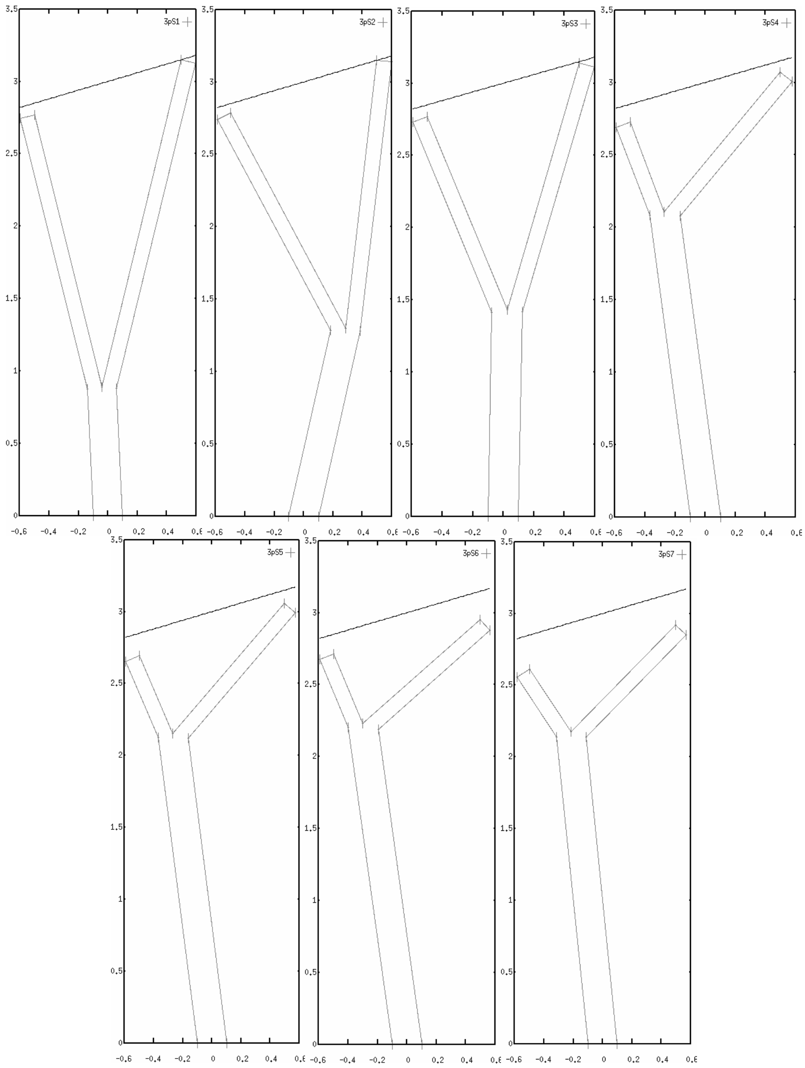

Fig. 5. Shapes of the 7 selected designs, from 1 (left) to 7 (right), multi-point receiver case.

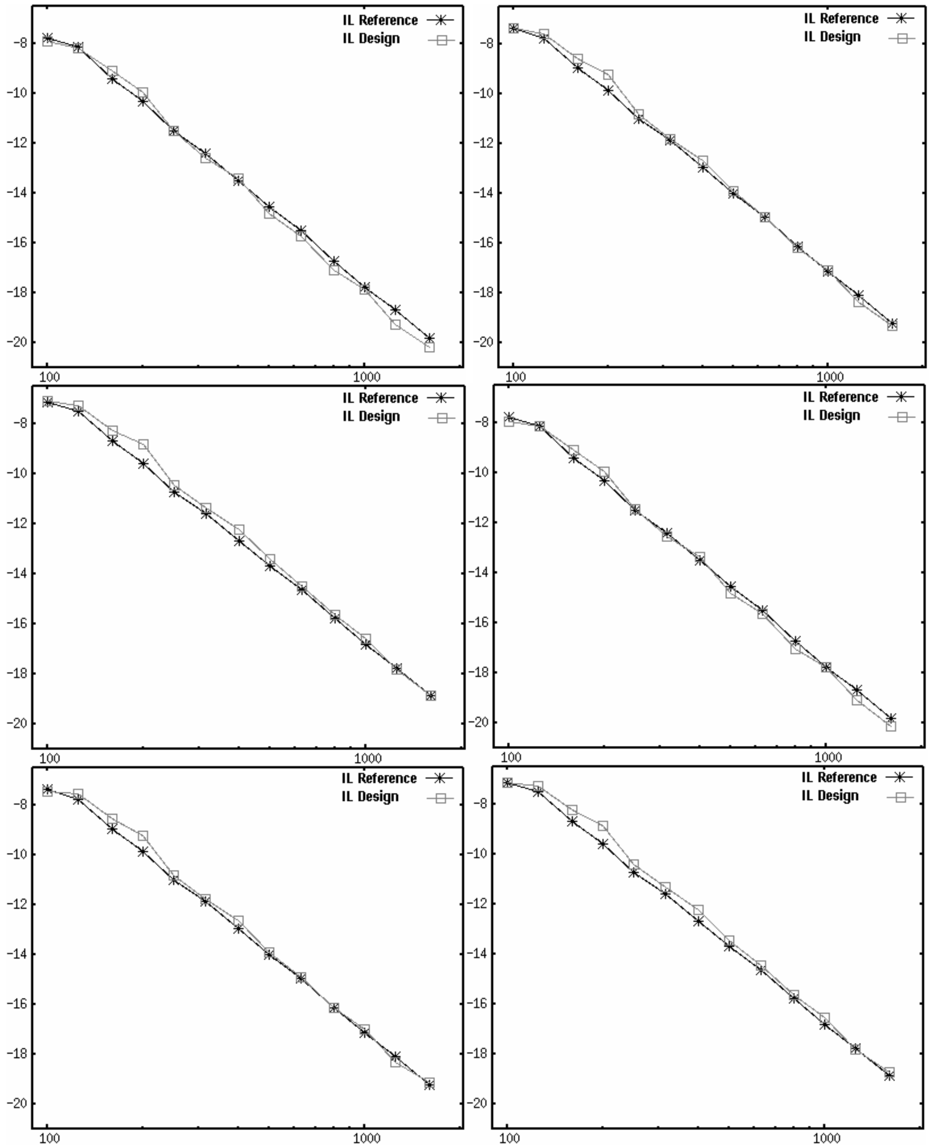

Fig. 6. Insertion loss (IL) in the third octave band centre frequency of barrier design (square) and reference (crossed lines). From left to right and up to down, the first three graphics include the best single-point design and the last three graphics the best multi-point design in terms of F1, being the reference curves those corresponding to receiver points 1, 2 and 3 respectively in each case of the 4.5-height straight barrier. (Frequencies (Hz) in log-scale in x-axis and IL values (dbA) in y-axis)

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