Cost optimisation of noise control for industrial buildings

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ABSTRACT
The acoustic design of noise control treatments for industrial buildings should consider the costs of materials and construction as key design parameters. However, reducing the cost of the acoustic design is often given a lower priority than is given to the primary design requirement of achieving the noise level goals. An effective method to reduce the overall costs of the noise control treatments for an industrial building is to use engineering optimisation techniques. The selection of noise treatments can be undertaken by a computer based on the constraint that the noise control goals must be met, but with the deliberate intention to minimise the overall noise control cost. An engineering optimisation technique suitable for this application is the Genetic Algorithm. This paper demonstrates a method of using Genetic Algorithms to minimise the cost of noise control treatments for an industrial building with a variety of available wall and roof cladding materials.

1. INTRODUCTION
The design of modern industrial buildings usually considers capital cost as one of the primary concerns. Construction materials are carefully selected by architects and engineers to achieve the best value-for-money balance between performance and cost for many design parameters including structural strength, material lifetime, buildability, thermal insulation properties, aesthetics and so on. The capital cost of acoustic treatments to a new industrial building should be no exception. It is possible to balance the acoustic performance needs with the requirement to minimise the cost of noise control materials, but to do so requires a robust computational technique, which will usually be much more successful than merely relying on a designer's intuition or personal preferences.

2. VALUE MANAGEMENT FOR NOISE CONTROL
Acoustic designs for industrial buildings are very sensitive to the assumed sound power levels of the noise-generating plant and equipment to be housed within them. The cost of conservatism in acoustic designs is often poorly understood by the design team (Speakman, 2007) because the project managers, quantity surveyors, architects, structural engineers, etc. often do not readily understand acoustic principles such as the Mass Law and Sabine's Law and the effects these have on the acoustic outcome. Consideration of noise control during the design phase can provide substantial dividends for projects by reducing the risk of the costs of dealing with complaints or retro-fitting noise control treatments in future.

3. ACOUSTIC DESIGN BY ENGINEERING OPTIMISATION
Some acoustic design problems are amenable to analysis by linear or non-linear optimisation techniques (Waley & Sarker, 1998). However, discrete numerical optimisation techniques are useful for complex acoustic design tasks entailing many noise sources, since 'off-the-shelf' noise control treatment devices are often available in a range of various models and sizes, which gives several different available values of Insertion Loss (and corresponding item cost) from which to choose to attenuate each of the noise sources.

Discrete optimisation methods are well suited to problems in which the solution being sought is one of a number of objects in a finite set (Nocedal & Wright, 1999), such as the selection of available noise treatments from one or more suppliers. In particular, Genetic Algorithms are well suited for solving discrete optimisation problems, especially in combinatorial situations, because of their ability to handle large numbers of variables, and they can usually find the global optimum solution with a high probability (Rao, 1996). The Genetic Algorithm method is particularly useful for the current example since it can be used to optimise the design to achieve the final target overall noise level while minimising the overall total cost.

4. GENETIC ALGORITHMS
Genetic Algorithms (GAs) are based on Darwin's principle of natural selection by mimicking the evolution of life. The procedure emulates the process of evolution, by using suitably sized populations, randomisation,

reproduction, crossover and mutation. A GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximises the overall 'fitness' (ie. minimises the cost function) (Haupt & Haupt, 2004). The algorithm therefore attempts to mimic the evolution of life by using genetic recombination in a gradual procedure which leads to maximisation of the 'fitness' of the chromosome. The Genetic Algorithm proceeds with an initial population of individuals. Each individual represents a potential solution to the problem being investigated, and each individual is evaluated in terms of its fitness. Some individuals are modified to form new individuals, either by mutation or by crossover, which creates new individuals by combining parts from two separate individuals. These new individuals (offspring) are then evaluated for their fitness, and the next population is formed by selecting the fittest individuals from both the parent and the offspring populations (Gen & Cheng, 2000). The basic procedure is as follows:

1. Commence with an initial population of trial design vectors
2. Combine some of the 'fittest' examples with a limited degree of randomisation, introducing crossover of genetic information from the parents to create the next generation of design vectors
3. Introduce some mutation into the chromosomes of the offspring, with a controlled degree of randomisation
4. Go to Step 2 and repeat for a pre-set maximum number of generations.

Some of the benefits of the method over other optimisation techniques, for combinatorial optimisation problems are:

- It is computationally efficient, because it is not a 'brute force' or an exhaustive method, meaning that only a small fraction of all possible combinations need to be evaluated
- It is not a gradient based method, which is a significant advantage in combinatorial optimisation problems because of the discrete variables and discontinuities in the objective (fitness) function.

In Genetic Algorithms, the design variables are represented as strings of binary numbers, usually 0 and 1. The 'chromosome' is therefore a binary string representing the value that each of the variables have taken, which together forms a binary representation of the overall design vector.

In the current example of the design of an industrial building, the design vector 'chromosome' represents which specific noise control treatments are to be applied to each element of the building envelope, so that the entire bit string makes up the complete noise treatment strategy for the entire building.

5. MODEL SET-UP

The sound transmission attenuation of the construction materials were represented with the weighted sound reduction index (R_w). The R_w and the as-built capital cost of the construction materials are shown in Table 1. The costs are fictional and are purely for the purposes of demonstrating the method. In Table 1, the costs of the windows and the door are $0 because they are not included as variables in the optimisation.

The sound absorption properties of the internal lining materials were represented with the noise reduction coefficient (NRC). The NRC and the as-built capital cost of the construction materials are shown in Table 2.

The building shape and size and the distance to the receptor assumed for this example is shown in Figure 1. A correction was applied to the vertical noise sources and to the roof to account for the directivity and self-shielding in the direction of propagation toward the receptor. The corrections are shown in Figure 2.

Table 1. R_w and as-built cost of building external envelope construction materials

Material Type index #	Description	Cost $/m^2	R_w
0	opening	0	0
1	0.55 mm thk sheet steel	200	20
2	110mm thk pre-cast concrete panel	600	30
3	Strawboard	80	15

Material Type index #	Description	Cost $/m^2	R_w
4	Sound Absorbent Steel Partition, Steel both sides, perf one face, mineral wool in cavity	400	27
5	0.6mm steel + 50mm fibreglass	300	23
6	Cold-room sandwich panel	160	19
7	Door	0	11
8	Glazing	0	15

Table 2. NRC and as-built cost of internal sound absorptive lining of wall/roof cladding

Material Type Index #	Description	Cost $/m^2	NRC
0	reflective	0	0.01
1	polyester 25mm 32kg/m^3	50	0.75
2	polyester 50mm 32kg/m^3	90	0.9
3	polyester 50mm 48kg/m3	130	0.85
4	polyester 100mm 32kg/m^3	160	1.1
5	fibreglass 25mm 32kg/m^3	60	0.75
6	fibreglass 50mm 32kg/m^3	100	1
7	mineral wool 50mm 32kg/m^3	95	0.8
8	mineral wool 50mm 60kg/m^3	190	1
9	door	0	0.2
10	opening	0	1

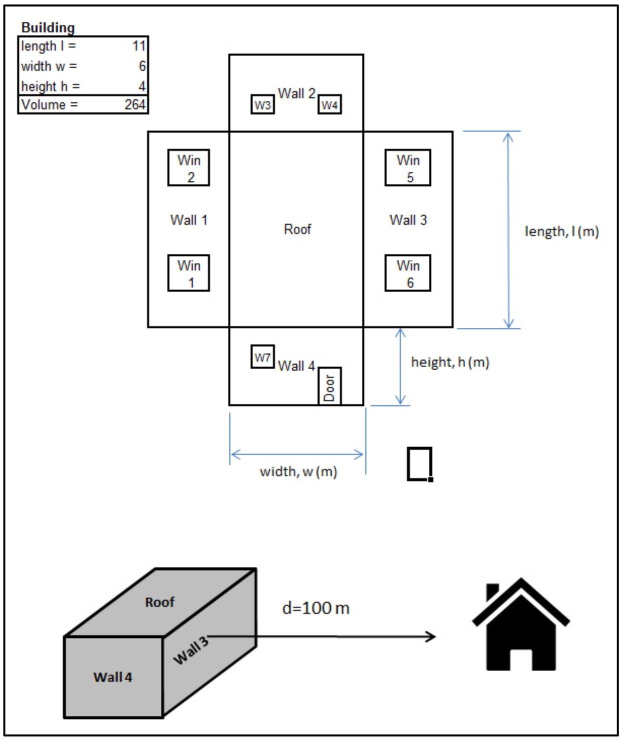

Figure 1. Industrial building size, shape and distance to receptor

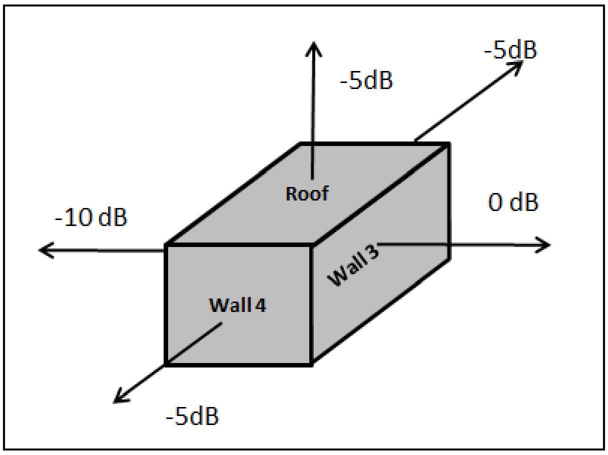

Figure 2. Corrections for directivity of building envelope components

6. MODELLING RESULTS

The optimised acoustic design for the wall and roof cladding and the internal absorptive lining is shown in Table 3 to Table 8, for the cases of the target design noise level being 45, 46, 47, 48, 49 & 50dB(A) respectively. In each case 4 representative answers for each target noise level case are given. In each case, the optimal result is displayed in **bold**. In some cases, the optimal result was repeated several times during the calculation runs, as demonstrated in Table 8 by the results presented for the case of 50 dB(A) limits, where the lowest cost case was calculated to be $28,832 for two non-sequential calculation runs. This trend was observed for several chosen values of target design noise level, implying that this level was possibly the global minimum for that target noise level minimum.

Table 3. Optimised Results for Target Noise Level = 45 dB(A)

Element	Result 1		Result 2		Result 3		Result 4	
	R_w type	NRC type	R_w type	NRC type	R_w type	NRC type	R_w type	NRC type
Wall 1	**3**	**4**	3	4	3	4	3	4
Wall 2	**3**	**4**	3	4	1	6	3	6
Wall 3	**5**	**4**	4	4	5	4	5	4
Wall 4	**3**	**4**	3	6	6	4	1	4
Roof	**6**	**4**	6	4	6	4	1	4
L_{rec} (dBA)	45.0		45.0		44.9		44.9	
Cost $	$27,680	$31,158	$31,280	$29,960	$32,000	$29,888	$32,840	$29,897
Total Cost	**$58,838**		$61,240		$61,888		$62,737	

Table 4. Optimised Results for Target Noise Level = 46 dB(A)

Element	Result 1		Result 2		Result 3		Result 4	
	R_w type	NRC type	R_w type	NRC type	R_w type	NRC type	R_w type	NRC type
Wall 1	**3**	**4**	3	4	3	4	3	4
Wall 2	**3**	**6**	3	4	3	4	3	4
Wall 3	**6**	**4**	6	6	1	6	6	4
Wall 4	**3**	**4**	3	4	3	6	3	6
Roof	**3**	**4**	6	6	6	6	3	4
Lrec (dBA)	46.0		45.9		45.9		45.9	
Cost $	$17,360	$29,939	$22,640	$25,247	$24,080	$24,003	$17,360	$29,996
Total Cost	**$47,299**		$47,887		$48,083		$47,356	

Table 5. Optimised Results for Target Noise Level = 47 dB(A)

Element	Result 1		Result 2		Result 3		Result 4	
	R_w type	NRC type	R_w type	NRC type	R_w type	NRC type	R_w type	NRC type
Wall 1	3	1	3	2	**3**	**6**	3	6
Wall 2	3	2	3	1	**3**	**6**	3	6
Wall 3	1	4	6	4	**1**	**6**	5	2
Wall 4	3	6	3	6	**3**	**6**	3	2
Roof	3	4	3	4	**3**	**6**	3	6
Lrec (dBA)	46.9		46.9		46.9		47.0	
Cost $	$18,800	$24,682	$17,360	$25,232	$18,800	$20,576	$22,400	$20,028
Total Cost	$43,482		$42,592		**$39,376**		$42,428	

Table 6. Optimised Results for Target Noise Level = 48 dB(A)

Element	Result 1		Result 2		Result 3		Result 4	
	R_w type	NRC type	R_w type	NRC type	R_w type	NRC type	R_w type	NRC type
Wall 1	3	6	3	1	3	2	**3**	**6**
Wall 2	3	1	3	6	3	1	**3**	**2**
Wall 3	6	1	6	6	6	6	**3**	**6**
Wall 4	3	6	3	6	3	6	**3**	**6**
Roof	3	6	3	2	3	2	**3**	**6**
Lrec (dBA)	47.9		48.0		48.0		47.9	
Cost $	$17,360	$17,749	$17,360	$18,193	$17,360	$18,534	$14,480	$20,384

Element	Result 1		Result 2		Result 3		Result 4	
	R_w type	NRC type	R_w type	NRC type	R_w type	NRC type	R_w type	NRC type
Total Cost	$35,109		$35,553		$35,894		**$34,864**	

Table 7. Optimised Results for Target Noise Level = 49 dB(A)

Element	Result 1		Result 2		Result 3		Result 4	
	R_w type	NRC type	R_w type	NRC type	R_w type	NRC type	R_w type	NRC type
Wall 1	3	6	**3**	**6**	3	1	3	6
Wall 2	3	1	**3**	**6**	3	1	3	5
Wall 3	3	1	**3**	**6**	3	6	3	1
Wall 4	3	6	**3**	**6**	3	2	3	2
Roof	3	6	**3**	**1**	3	6	3	6
Lrec (dBA)	48.8		**48.9**		48.9		48.9	
Cost $	$14,480	$17,761	**$14,480**	**$17,369**	$14,480	$17,559	$14,480	$17,779
Total Cost	$32,241		**$31,849**		$32,039		$32,259	

Table 8. Optimised Results for Target Noise Level = 50 dB(A)

Element	Result 1		Result 2		Result 3		Result 4	
	R_w type	NRC type	R_w type	NRC type	R_w type	NRC type	R_w type	NRC type
Wall 1	**3**	**1**	3	1	3	6	**3**	**6**
Wall 2	**3**	**2**	3	1	3	2	**3**	**2**
Wall 3	**3**	**6**	3	1	3	5	**3**	**1**
Wall 4	**3**	**1**	3	2	3	1	**3**	**1**
Roof	**3**	**1**	3	2	3	5	**3**	**1**
Lrec (dBA)	**50.0**		49.9		50.0		**50.0**	
Cost $	**$14,480**	**$14,352**	$14,480	$15,150	$14,480	$15,372	**$14,480**	**$14,352**
Total Cost	**$28,832**		$29,630		$29,852		**$28,832**	

As shown in Table 3 to Table 8, the optimisation algorithm always yields a resultant noise level less than or equal to the target design noise level limit.

7. DISCUSSION

The probability of a Genetic Algorithm finding a global optimum depends on several factors including the 'smoothness' of the cost function's 'surface'. When a Genetic Algorithm is used, the procedure must be repeated numerous times with different initial guesses, to improve the likelihood of finding a global optimum.

In the current example, the optimisation routine needed to be run approximately 20 times before confidence was gained that a global optimum (or near to) had been achieved. Depending on the target noise level limit assigned, the algorithm typically converged between 2000 and 10000 generations in each calculation run. The general trend observed was that the higher the target noise level, the higher was the number of generations before the genetic algorithm converged. The process sometimes converged to a local sub-optimal minimum and failed to converge within the pre-set maximum number of iterations, and on a few occasions it did not converge at all. It is therefore expected that the 'surface' of the cost function is likely to have multiple local minima, and may have a low probability of finding the globally optimal minimum.

It was observed that the optimisation result was quite sensitive to the starting point of the search. In general, if the starting point array of cladding and inner lining resulted in a noise level lower than the target noise level limit, then the algorithm readily approached the global minimum. If the starting point array resulted in a noise level higher than the limit, then the algorithm always returned a result where the noise level met the limit, but the costs were sometimes far higher than the global minimum (by eg. 50 or 100%). An explanation for this trend was not readily apparent.

8. CONCLUSIONS

The Genetic Algorithms method has been clearly demonstrated to be a very useful method of achieving a complicated acoustic design optimisation task. The method is found to be a versatile and valuable tool for the purposes of optimising the acoustic design of an industrial building, by achieving the noise control outcomes for the minimum cost.

9. LIMITATIONS OF THE STUDY AND FURTHER WORK

The example case study given has been presented without overly complicated acoustic parameters, in order to demonstrate the method as clearly as possible. Most notably, the calculations were performed with single-number values for Sound Power (L_w dB(A)), Transmission Loss (R_w) and sound absorption coefficient (NRC). Also, the case study has not considered other factors such as shielding or directivity of noise sources within the building, and so on. Nevertheless, it is clear that the method can be readily extended into the frequency domain and utilised in a real-world situation, with spectral information of noise sources and mitigation, spatially distributed noise-sensitive receivers and noise sources, as well as incorporating the propagation attenuation by shielding, ground & air absorption and so on. These will be the goals for further development of this methodology.

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