Optimisation of noise control treatments for staged noise management programs using genetic algorithms

Dave Davis

Parsons Brinckerhoff, Queensland, Australia

ABSTRACT

Maximising the cost-effectiveness of noise mitigation treatments for industrial facilities is usually a prime consideration. Accordingly, the selection of noise control treatments for individual noise sources can be optimised to maximise the total value-for-money of the overall noise mitigation treatment program. Additionally, it may also be desirable to stage the implementation of the plant's noise reduction program into several phases, for instance if the noise mitigation funding is only available as an annual budget allowance. A method is proposed to achieve these goals using Genetic Algorithms. An example case study is provided to illustrate the procedure. A hypothetical industrial plant with 100 noise sources is investigated, and the procedure is demonstrated with an example scenario of a target total noise level reduction, and a fixed annual budget allowance for noise mitigation treatments.

INTRODUCTION

Most engineering design problems are required to achieve the desired outcome for an efficient overall cost.

In the case of designing a noise control treatment program for an industrial plant with many individual noise sources, it may be prohibitively expensive to install all of the required noise control treatments *en masse*. Consequently it may be necessary to implement the plant noise mitigation program in stages, by implementing whatever noise control treatments are affordable according to a staged program, for example within an annual budget allowance.

In this case, it is likely to be desirable to achieve the greatest possible overall noise reduction at each of the stages within the budgetary constraints, but particularly so for the first stage, in order to manage the perceptions of the program's initial success and expectations of the final outcome.

It would be advantageous to achieve a significant reduction of the overall site's noise emissions in the first stage of the noise reduction program, in which only a few noise sources are treated, even though the overall criteria will not be met until later stage(s). This can be achieved by the careful selection of noise treatments to be implemented in the first stage, which can maximise the noise reduction achievable within the first term's budget.

Thus the implementation of a site's noise mitigation treatment program can be optimised not only in terms of overall cost-effectiveness, but also in terms of maximising the total noise reduction achieved in each stage of the program.

Design by engineering optimisation

Although nonlinear optimisation techniques can be used in some applications of noise analysis (Waly & Sarker 1998), linear or non-linear optimisation techniques are too simplistic to deal with complex engineering problems (Sato et al 2004).

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 for 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).

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).

Furthermore, the Genetic Algorithm method is particularly useful for this current example application since it can be used to optimise the design in both of the required directions: firstly to achieve the final target overall noise level while minimising the overall total cost, and then to maximise the incremental noise level reduction achievable with a fixed budget for each stage of the noise management program.

Furthermore, if the plant is existing, Genetic Algorithms can also be used to help identify the sound power levels of the various existing noise sources within a complicated sound field (Lan & Chiu 2008).

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 mimick 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 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 not 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 case of a noise management program, the design vector 'chromosome' represents which specific noise control treatments are to be applied to each noise source, so that the entire bit string makes up the complete noise management program of the entire plant.

Inclusion of Constraints

The Genetic Algorithm method maximises the objective (fitness) function. If the optimisation task is to find the minimum of the objective function, the function simply needs to be negated. However, since the GA method is an unconstrained optimisation routine, there is no way to implicitly include boundary contraints. Constraints must therefore be handled by the exterior penalty function method (Rao 1996).

A simple penalty function is to sum the squares of the violation of the constraints and multiply by a constant. The unconstrained function $f(\mathbf{X})$ can be transformed to a constrained function $F(\mathbf{X})$as follows:

Minimise

$$F(\mathbf{X}) = f(\mathbf{X}) + P\left[\sum_k \left(\max\left(0, g_k(\mathbf{X})\right)\right)^2 + \sum_l \left(h_l(\mathbf{X})\right)^2\right] \qquad [1]$$

where $g_k(\mathbf{X})$ are the inequality constraint(s) and $h_l(\mathbf{X})$ are the equality constraint(s).

$$g_k(x) \leq 0 \qquad k = 1, \ldots p \qquad [2]$$

$$h_l(x) \leq 0 \qquad l = 1, \ldots q \qquad [3]$$

and P is a constant, known as the *penalty parameter*. Usually P is deliberately forced to be a large number.

EXAMPLE CASE STUDY

The example case study is a hypothetical industrial plant with 100 noise sources. The sound power levels of the noise sources were randomly assigned, varying between 75 and 120dB re 10^{-12}W as shown in Figure 1.

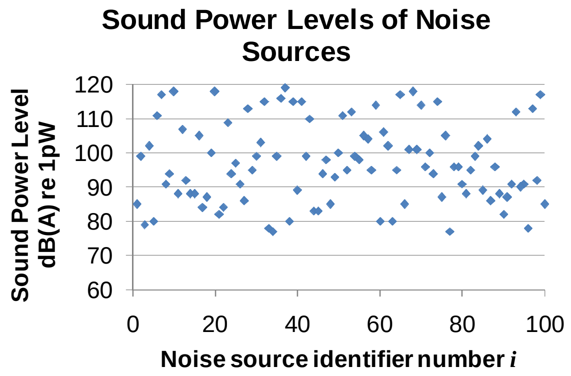

Figure 1. Sound Power Levels of noise sources (dB re 1pW)

A hypothetical schedule of cost and Insertion Loss [IL] for the available noise control treatments was developed as a basis for the optimisation exercise, shown numerically in Table 2 and graphically in Figure 1. For this example case study, three noise control treatment options exist for each noise source, the cost of which depends on the noise source's original untreated sound power level.

Table 2. Noise control treatment options

Treatment option j	IL (dB)	Cost ($) depending on PWL				
		Sound Power Level dB re 10^{-12}W				
		75-85	85-95	95-105	105-115	>115
0	0	0	0	0	0	0
1	5	2k	3k	4,5k	6,750	10,125
2	10	4,5k	6,75k	10,125	15,188	22,781
3	15	10k	15k	22,5k	33,750	50,625

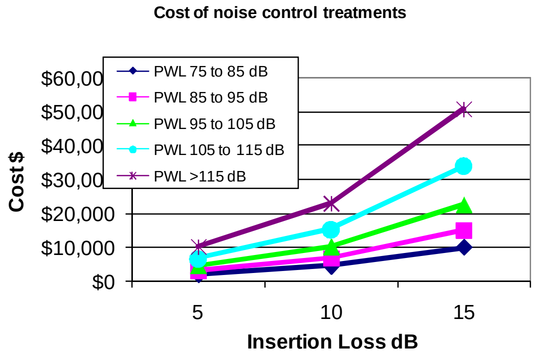

Figure 1. Noise control treatment options

The length of the binary string design vector is determined as follows: if each design variable $x_i, i = 1, 2, \ldots, n$ is represented as a binary string of length b bits, then the design vector's total length will be nb.

Since there are 4 noise control treatment options available, the variable can be represented by a 2-bit string as shown in Table 2.

Table 2. Binary representation of noise treatment option

j (decimal)	0	1	2	3
j (binary)	00	01	10	11

Since all of the variables' values can be represented by a string of 2 bits or less, with a total of 100 noise sources, the length of the chromosome (the binary representation of the design vector) will be 2*100 = 200 bits.

An example segment of a chromosome is shown in Table 3.

Table 3. Example chromosome segment

Noise source number	i-2	i-1	i	i+1	i+2
variable	x_{i-2}	x_{i-1}	x_i	x_{i+1}	x_{i+2}
noise treatment option j (decimal)	0	3	1	0	2
chromosome segment	0 0	1 1	0 1	0 0	1 0

Example scenario

The above hypothetical industrial plant with its 100 noise sources will be investigated for the case of a given overall noise reduction target with the aim of minimising the total cost. The noise management program will then be further investigated to determine the yearly noise reduction achievable with a fixed annual noise mitigation budget allowance.

Inputs:

- Target overall noise level reduction: 6.03dB
- Annual budget: $200,000
- Number of noise sources = 100

The optimisation problem is therefore:

- Objective function to be minimised = overall cost
- Constraint(s): target noise level must not be exceeded

In formal notation, the cost function to be minimised is:

$$f(\mathbf{X}) = \sum_{i=1}^{n} \mathbf{C}(\mathbf{X})_i \quad [4]$$

Where $\mathbf{C}(\mathbf{X})$ is the vector representing the costs of noise treatments for each noise source.

The constraint is introduced with the penalty function as follows:

Minimise:

$$F(\mathbf{X}) = \sum_{i=1}^{n} \mathbf{C}(\mathbf{X})_i + P\left[\left(\max\left[0, \left(L_{w_{tot}} - L_{w_0}\right)\right]\right)^2\right] \quad [5]$$

where $L_{w_{tot}}$ is the total sound power level of the entire plant with treated noise sources, for each specific individual within the GA population (eq. [6]), and $L_{w_0}$is the total sound power level of the entire plant before any noise treatments (eq. [7]).

$$L_{w_{tot}} = 10\log\sum_{i=1}^{n} 10^{L_{w_{i_j}}/10} \quad [6]$$

where $L_{w_{i_j}}$ is the sound power level of noise source i with treatment j, and

$$L_{w_0} = 10\log\sum_{i=1}^{n} 10^{L_{w_{i_0}}/10} \quad [7]$$

where $L_{w_{i_0}}$ is the untreated sound power level of all noise sources (ie. $j = 0$ for all noise sources i).

Results:

The evolution of the Fitness function for the optimal calculation run is shown in Figure 2.

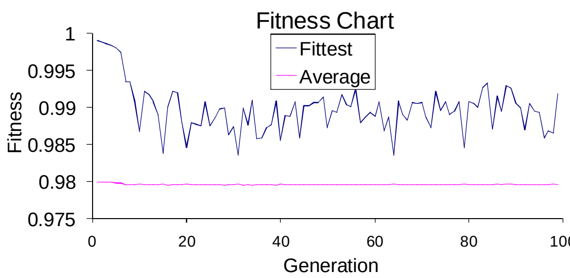

Figure 2. Evolution of the Fitness function

The results of the (assumed to be) successful optimisation GA calculation run are:

- Total cost of noise mitigation program: $442,375
- Number of noise sources to be treated: 47
- Resultant overall noise level reduction: 6.04dB

The top 25 noise sources that will have the highest sound power levels after the noise management program is completed, is shown in Figure 3.

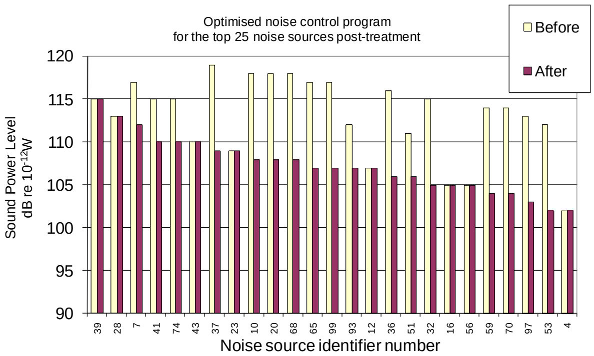

Figure 3. Top 25 noise sources post-treatment

The optimised noise treatment options for each of the noise sources are shown in Table 4.

Table 4. Optimised noise control treatment program

Noise Source *i* vs. Treatment option *j*							
i	*j*	*i*	*j*	*i*	*j*	*i*	*j*
1	**0**	26	**1**	51	**1**	76	**1**
2	**0**	27	**0**	52	**0**	77	**2**
3	**0**	28	**0**	53	**2**	78	**0**
4	**0**	29	**0**	54	**1**	79	**0**
5	**0**	30	**1**	55	**0**	80	**0**
6	**2**	31	**1**	56	**0**	81	**0**
7	**1**	32	**2**	57	**1**	82	**2**
8	**0**	33	**0**	58	**1**	83	**0**
9	**0**	34	**1**	59	**2**	84	**2**
10	**2**	35	**2**	60	**0**	85	**1**
11	**1**	36	**2**	61	**2**	86	**1**
12	**0**	37	**2**	62	**0**	87	**0**
13	**1**	38	**0**	63	**0**	88	**1**
14	**0**	39	**0**	64	**0**	89	**0**
15	**0**	40	**0**	65	**2**	90	**0**
16	**0**	41	**1**	66	**1**	91	**0**
17	**0**	42	**0**	67	**0**	92	**0**
18	**0**	43	**0**	68	**2**	93	**1**
19	**1**	44	**0**	69	**1**	94	**0**
20	**2**	45	**0**	70	**2**	95	**0**
21	**0**	46	**1**	71	**0**	96	**1**
22	**0**	47	**1**	72	**1**	97	**2**
23	**0**	48	**0**	73	**1**	98	**0**
24	**0**	49	**1**	74	**1**	99	**2**
25	**0**	50	**0**	75	**1**	100	**1**

Once the required noise mitigation schedule has been determined as shown in Table 4, the second step is to maximise the noise reduction achievable in each year of the staged program according to the annual budgets. For this step, the variable is a single-bit string representing true/false statements in answer to the question: "will this noise source be treated in this year's annual budget?"

The second optimisation problem is formulated as follows:

- Objective (Fitness) function to be maximised = yearly total noise level reduction
- Constraint(s) = fixed incremental budget

The results are shown in Table 5.

Table 5. Summary of incremental noise management program

Year	1	2	3
Budget	$200,000	$200,000	$200,000
Expenditure	$200,000	$198,875	$43,500
Incremental noise level reduction achieved	2.11 dB	3.67 dB	0.26dB
Total noise level reduction achieved		6.04dB	

The detailed noise management program showing the yearly noise treatment schedule is summarised in Table 6.

Table 6. Optimised noise control treatment program

Noise Source *i* vs. Year of treatment *y*							
i	*y*	*i*	*y*	*i*	*y*	*i*	*Y*
1		26	**3**	51	**3**	76	**2**
2		27		52		77	**1**
3		28		53	**2**	78	
4		29		54	**1**	79	
5		30	**1**	55		80	
6	**2**	31	**1**	56		81	
7	**1**	32	**2**	57	**1**	82	**3**
8		33		58	**2**	83	
9		34	**1**	59	**2**	84	**3**
10	**1**	35	**1**	60		85	**2**
11	**2**	36	**2**	61	**1**	86	**2**
12		37	**1**	62		87	
13	**1**	38		63		88	**3**
14		39		64		89	
15		40		65	**1**	90	
16		41	**2**	66	**1**	91	
17		42		67		92	
18		43		68	**2**	93	**1**
19	**3**	44		69	**3**	94	
20	**1**	45		70	**1**	95	
21		46	**1**	71		96	**2**
22		47	**1**	72	**1**	97	**2**
23		48		73	**2**	98	
24		49	**1**	74	**2**	99	**2**
25		50		75	**1**	100	**1**

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 10 times before confidence was gained that a global optimimum had been achieved. The process sometimes converged to a local sub-optimal minima and failed to emerge within the pre-set maximum number of iterations, and on a few other 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 not have a well-definied globally optimal minima.

The evolution of the Fitness function for two of the sub-optimal runs are shown in Figures 4a and 4b.

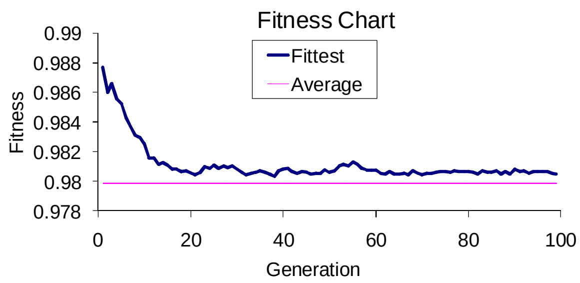

Figure 4a. Non-optimal convergence example (a). Total noise treatment cost = $510,218.75

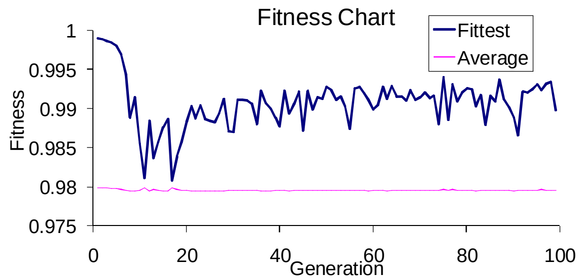

Figure 4b. Non-optimal convergence example (b). Total noise treatment cost = $564,468.75

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 a staged noise management program, firstly in terms of overall cost effectiveness of the entire program, and also for maximising the noise reduction benfit of the intermediate implementation stages.

These two design goals are subtly different, whereby in fact their objective functions and constraints are reversed relative to each other, and the Genetic Algorithms method is shown to be readily adaptable to be useable in both cases.

LIMITATIONS OF THE STUDY AND FURTHER RESEARCH

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 noise sources' sound power levels and the noise mitigation treatments' Insertion Losses were assigned a single numerical value without any sound frequency information. Also, the case study investigates only the total sound power level of the plant, and does not consider the added complexity of possible variability in noise source spatial locations relative to noise sensitive receiver(s).

Nevertheless, the method can be readily utilised in a real-world situation, with spatially distributed noise-sensitive receivers and noise sources, spectral information of noise sources and mitigation, as well as incorporating the propagation attenuation by shielding, ground & air absorption and so on.

REFERENCES

Gen M & Cheng R 2000, *Genetic algorithms and engineering optimization*, Volume 56, Wiley-IEEE, New York, USA

Haupt RL & Haupt SE 2004, *Practical Genetic Algorithms, (2nd ed.)*, Wiley Interscience, New Jersey, USA

Lan TS & Chiu MC 2008, 'Identification of noise sources in factory's sound field by using genetic algorithm' Applied Acoustics, Vol 69 pp 733-750

Nocedal J & Wright SJ 1999, *Numerical Optimization (2nd ed.)*, Springer, New York

Rao SS 1996, *Engineering Optimization – Theory and Practice (3rd ed.)*, Wiley-Interscience, USA

Sato S, Hayashi T, Takizawa A, Tani A, Kawamura H & Ando Y 2004, 'Acoustic Design of Theatres Applying Genetic Algorithms' Journal of Temporal Design in Architecture and Environment Vol. 4 No. 1.

Waly SM & Sarker BR 1998, 'Noise reduction using nonlinear optimization modeling', Computers & Industrial Engineering Vol 35, 1-2, October 1998, pp 327-330