

Maximising rates of productivity at mine, quarry and construction sites using engineering optimisation and Monte-Carlo simulation

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ABSTRACT

Industrial activities comprised of fixed and mobile noise sources such as mines, quarries and construction sites often operate under environmental noise limitations that can restrict site activity at certain times. The noise immission levels at receptors vary continuously due to unsteady noise emissions of plant and/or because of changes in mobile equipment location and/or orientation and also because of the continually changing attenuation properties of the atmosphere affecting the sound propagation. These sites often want to maximise their production rates utilising as much of their fleet and equipment inventory as possible while still complying with their environmental noise limits. This paper presents a method to maximise the size of the operating fleet within the site's environmental noise constraints, taking into account the inherent variability of noise sources using engineering optimisation and Monte-Carlo simulation.

1 INTRODUCTION

It is highly desirable to maximise the productivity of activity occurring on a site with numerous mobile and stationary noise sources such as a mine, quarry or construction site while still complying with the noise limits. In acoustics terms, this usually means maximising the number of noise sources operating simultaneously while achieving the noise immission criteria at the noise sensitive receptors.

Sound propagation from a stationary noise source can be influenced by two types of variability: fluctuations in the noise sources' noise emissions and variations in atmospheric attenuation, barrier attenuation and ground absorption due to changes in meteorological conditions. Propagation from a mobile noise source is further influenced by changes in the distance attenuation and the corresponding changes in the atmospheric absorption, ground absorption and barrier shielding that occurs as a result of the noise source changing location.

It is possible to optimise the number of noise sources actively operating on site at any point in time in order to maximise the site's overall productivity using engineering optimisation techniques. For situations with numerous noise sources where each source can be in either of two modes ("on" or "off") a combinatorial optimisation technique such as the Genetic Algorithm or the Evolutionary Algorithm can be used effectively to maximise the site productivity (Davis, 2016). The Genetic Algorithm and the Evolutionary Algorithm are quasi-random metaheuristic search methods that start with a population of initial "guesses" and progressively refine the search to find "good" solutions, although it can never be guaranteed that the "best" (global optimum) solution has been found (Blum and Roli, 2003).

The basic version of the Evolutionary Algorithm can be used to optimise deterministic situations where the variables can only assume quantities from a finite set of available inputs. However the Evolutionary Algorithm can be modified to optimise situations where the variables can be defined as uncertain quantities, that is a variable can assume any value based on a known distribution. This type of optimisation can be very useful in environmental noise control problems, when the noise immission at a receptor is variable because the noise sources' emissions and the propagation losses are variable but the noise level target criteria are fixed numerical values.

Optimisation software that runs the Evolutionary Algorithm with uncertain variables will typically form the initial population of random guesses using a sampling technique similar to the Monte Carlo method. The purpose of this paper is to demonstrate how this technique can be applied to the problem of maximising the work rate of an industrial operation while still complying with environmental noise constraints.



2 VARIABILITY IN ENVIRONMENTAL NOISE GENERATION AND PROPAGATION

2.1 VARIABILITY IN NOISE SOURCE NOISE GENERATION

If a noise source generates variable noise emissions but the propagation path between the source and the receiver is perfectly stable, then the distribution of the source sound power levels and the received sound pressure levels at individual frequencies should be the same, as illustrated in Figure 1.



Figure 1: Received SPL variability due solely to source emission variability

2.2 VARIABILITY IN NOISE PROPAGATION

If the noise source emits steady constant noise emissions, the variability of the received SPL would be due solely to variability of propagation attenuation, as illustrated in Figure 2.



Figure 2: Received SPL variability due solely to atmospheric variability

2.3 COMBINED VARIABILITY IN ENVIRONMENTAL NOISE GENERATION AND PROPAGATION

If the noise source's noise emissions and the propagation path attenuation both exhibit variability, the variability in the received SPL will be due to the combination of both causes of variability acting together as illustrated in Figure 3. The result is a bivariate probability density function.



Figure 3: Received SPL variability due to the combination of source emission variability and propagation varia-

bility

3 BIVARIATE NORMAL DISTRIBUTION

If two variables are normally distributed, the joint probability density function P of the combination of those two variables is shown in equation 1.

$$P(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} e^{\left[-\frac{z}{2(1-\rho^2)}\right]}$$
(1)

where

 σ_1, σ_2 are the Standard Deviations of populations 1 and 2 respectively,

$$z \equiv \frac{(x_1 - \mu_1)^2}{\sigma_1^2} - \frac{2\rho(x_1 - \mu_1)(x_2 - \mu_2)}{\sigma_1 \sigma_2} + \frac{(x_2 - \mu_2)^2}{\sigma_2^2}$$
(2)

 x_1, x_2 are the variable values of populations 1 and 2 respectively,

 μ_1, μ_2 are the means of populations 1 and 2 respectively

$$\rho \equiv \operatorname{cor}(x_1, x_2) = \frac{v_{12}}{\sigma_1 \sigma_2} \tag{3}$$

is the correlation of x_1 and x_2 and v_{12} is the covariance.

A scatter plot showing an example two-dimensional probability density function (PDF) is shown in Figure 4.

Source (Wikimedia Commons, 2017) Figure 4: Example bivariate (two-dimensional) probability density function with means = 0

3.1 Two-dimensional variability in environmental noise levels

In theory, the variability of the sound power of a noise source may follow any distribution. Also, the variability of the attenuation of sound propagation may also follow any distribution, and the distribution may also change with time due to various factors. However, for the purpose of demonstrating the application of the Monte Carlo-modified Evolutionary Algorithm, it is assumed that both of these variables are normally distributed.

If both the sound power level and the propagation attenuation variables are normally distributed, the joint bivariate probability density function will be

$$P(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2} e^{-\left[\frac{(x_1-\mu_1)^2}{2\sigma_1^2} + \frac{(x_2-\mu_2)^2}{2\sigma_2^2}\right]}$$
(4)

which is simply the product of the two PDFs for x_1 and x_2 (Bertsekas and Tsitsiklis, 2002).

As an example, for two independent functions with both means $\mu_1 = \mu_2 = 0$ and standard deviations $\sigma_1 = 1.2$, $\sigma_2 = 1.5$ the separate and joint PDFs are shown in Figure 5.

















Figure 5: Example bivariate probability density function with means = 0, σ_1 = 1.2, σ_2 = 1.5

An example scatter plot of the received SPL from a single noise source showing the variability due to an assumed normally distributed SWL and normally distributed propagation attenuation is shown in Figure 6.



Figure 6: Scatter plot of example variability in noise received due to variable noise source noise emissions and variable propagation attenuation

It is also common for the sound emissions of a typical noise source to be variable in each spectral frequency band, as shown in Figure 7.







4 OPTIMISATION OBJECTIVE

The goal of the optimisation calculations is to determine the minimum number of noise sources that need to be removed or "turned off" at a site that typically has numerous simultaneous active noise sources, in order for the received SPL at all receivers to comply with the criteria for a desired percentage of the total sample set, as shown in Figure 8. In practice, the sample set will consist of the continuously recorded noise monitoring data which is stored in discrete blocks at regular interval units of time.





5 EXAMPLE 1 – VARIABLE SOUND POWER LEVEL; NON-VARIABLE PROPAGATION ATTENUATION

In order to demonstrate the optimisation of maximising the number of variable noise sources with static (non-variable) propagation attenuations, an example case study is presented below using randomly generated data for sound power levels and standard deviations for the noise sources, as shown in Figure 9. The propagation attenuation data between each source and each receiver is not provided since it was a large amount of data, however the values were generated as random numbers from 70 to 80 dB inclusive.

The parameters of the example scenario are as follows:

- Number of noise sources: 50
- Number of noise receivers: 10







5.1 Example 1a - Target compliance 90%

As shown in Figure 10 and Table 1, the Monte-Carlo modified Evolutionary Algorithm maximised the number of operating noise sources while complying with the noise criteria for at least 90% of the time at all receivers by removing 12 noise sources.



Figure 10: Noise sources active or shut down to achieve 90% compliance with the noise criteria at all receivers

Table 1: Predicted noise levels at receivers with noise sources maximised to achieve 90% compliance

Receiver ID No.	1	2	3	4	5	6	7	8	9	10
Criteria dB(A)	56	56	56	56	56	56	56	56	56	56
Mean SPL dB(A)	53.6	54.6	55.1	55.4	53.8	54.6	54.5	55.2	54.8	54.5
Exceedance of										
mean SPL dB(A)	-2.4	-1.4	-0.9	-0.6	-2.2	-1.4	-1.5	-0.8	-1.2	-1.5
% Compliance	100.0	99.7	98.1	90.1	100.0	100.0	100.0	96.8	99.8	100.0



5.2 Example 1b - Target compliance 95%

As shown in Figure 11 and Table 2, the Monte-Carlo modified Evolutionary Algorithm maximised the number of operating noise sources while complying with the noise criteria for at least 95% of the time at all receivers by removing 13 noise sources.



Figure 11: Noise sources active or shut down to achieve 95% compliance with the noise criteria at all receivers

Table 2: Predicted noise levels at receivers with noise sources maximised to achieve 95% compliance

Receiver ID No.	1	2	3	4	5	6	7	8	9	10
Criteria dB(A)	56	56	56	56	56	56	56	56	56	56
Mean SPL dB(A)	53.9	53.6	55.1	55.0	54.0	54.3	53.6	55.2	55.0	54.2
Exceedance of										
mean SPL dB(A)	-2.1	-2.4	-0.9	-1.0	-2.0	-1.7	-2.4	-0.8	-1.0	-1.8
% Compliance	100.0	100.0	98.5	99.3	100.0	100.0	100.0	96.7	99.0	100.0

5.3 Example 1c - Target compliance 99%

As shown in Figure 12 and Table 3, the Monte-Carlo modified Evolutionary Algorithm maximised the number of operating noise sources while complying with the noise criteria for at least 99% of the time at all receivers by removing 14 noise sources.



Figure 12: Noise sources active or shut down to achieve 99% compliance with the noise criteria at all receivers Table 3: Predicted noise levels at receivers with noise sources maximised to achieve 99% compliance

		Inpliance

Receiver ID No.	1	2	3	4	5	6	7	8	9	10
Criteria dB(A)	56	56	56	56	56	56	56	56	56	56
Mean SPL dB(A)	53.5	54.1	54.4	54.3	53.3	54.2	52.7	54.8	55.0	53.9
Exceedance of										
mean SPL dB(A)	-2.5	-1.9	-1.6	-1.7	-2.7	-1.8	-3.3	-1.2	-1.0	-2.1
% Compliance	100.0	100.0	100.0	100.0	100.0	100.0	100.0	99.8	99.3	100.0



6 EXAMPLE 2 – VARIABLE SOUND POWER LEVEL; VARIABLE PROPAGATION ATTENUATION

In order to demonstrate the optimisation of maximising the number of variable noise sources with variable propagation attenuations, an example case study is presented below using randomly generated data for sound power levels, propagation attenuation and standard deviations for both.

The parameters of the example scenario are as follows:

- Number of noise sources: 10
- Number of noise receivers: 4

The variability in the noise sources' sound power levels are shown in Table 4 and Figure 13.

Table 4: Mean and Standard Deviations of Sound Power levels of noise sources





Figure 13: Variability in Sound Power Levels

The variability in the propagation attenuation between the noise sources and receivers are shown in Table 5.

Table 5 [.] Mean and	Standard D	eviation of	attenuation	of sound	propagation	from sources	to receivers
	otanuaru D	Cviation of	allenuation	or sound	propagation	10111 3001003	10100010013

	Attenua	ations –	mean dE	3(A)	Attenuations – Standard Deviation dB(A)					
		Receive	ər ID		Receiver ID					
Source ID	1	2	3	4	1	2	3	4		
1	59	54	52	50	2.6	1.91	1.74	1.82		
2	55	59	60	56	2.58	1.98	2.18	2.12		
3	53	51	52	55	1.7	2.27	2.02	2.33		
4	54	56	57	54	1.68	2.11	1.93	1.91		
5	56	55	56	55	1.81	2.28	2.46	2.4		
6	50	57	50	50	2.01	2.04	2.62	2.23		
7	52	54	58	60	1.51	2.54	1.52	1.96		
8	60	50	52	52	1.66	2.46	1.81	2.35		
9	60	52	58	55	2.6	1.91	1.74	1.82		
10	58	54	53	58	2.58	1.98	2.18	2.12		



6.1 Example 2a - Target compliance 90%

As shown in Table 6, the Monte-Carlo modified Evolutionary Algorithm removed 3 noise sources (sources 7, 8 and 9) in order to achieve compliance at all receivers for at least 90% of the time.

Source ID	1	2	3	4	5	6	7	8	9	10
On/Off?	On On		On	On	On	On	Off	Off	Off	On
Receiver ID Nui	Receiver ID Number			1	2		3		4	
Criteria dB(A)	Criteria dB(A)		65		65		65	5	65	
Mean SPL dB(A	Mean SPL dB(A)			62.6		3.1	63	3.4	63.4	
Exceedance of mean SPL dB(A)		(A) ·	3.4	-2.9		-2.6		-2.6		
Probability of co	mpliand	e	9	98.0%	97.7%		92	2.0%	91.0%	6

6.2 Example 2b - Target compliance 95%

As shown in Table 7, the Monte-Carlo modified Evolutionary Algorithm removed 4 noise sources (sources 5, 7, 8 and 9) in order to achieve compliance at all receivers for at least 95% of the time.

Table	7' Na	nise	Sources	maximised	to achiev	e 95%	compliand	ce with	noise	criteria	at all	receivers
1 abic	1.11	0130	0001003	maximiscu			compliant		1030	ontona	aran	100010013

Source ID	1	2	3	4	5	6	7	8	9	10
On/Off?	On	n On Oi		On	Off	On	Off	Off	Off	On
Receiver ID Num	ver ID Number			1	2	2	3		4	
Criteria dB(A)	eria dB(A)			65		65	6	5	65	
Mean SPL dB(A)	lean SPL dB(A)			61.2	6	61.5	62	2.2	61.9	9
Exceedance of m	Exceedance of mean SPL dB(A)		(A)	-3.8		3.5	-2.8		-3.1	
Probability of compliance				99.5%	ę	99.8%	97	7.6%	98.4	4%

6.3 Example 2c - Target compliance 99%

As shown in Table 8, the Monte-Carlo modified Evolutionary Algorithm removed 5 noise sources (sources 3, 5, 7, 8 and 9) in order to achieve compliance at all receivers for at least 99% of the time.

Table 8: Noise Sources maximised to achieve 99% compliance with noise criteria at all receivers

Source ID	1	2	3	4	5	6	7	8	9	10
On/Off?	On	On	Off	On	Off	On	Off	Off	Off	On
Receiver ID Num	ID Number			1			3		4	
Criteria dB(A)	a dB(A)		65		65		65		65	
Mean SPL dB(A)	Mean SPL dB(A)		5	59.9		9.5	61.0		61.3	
Exceedance of m	Exceedance of mean SPL dB(A		(A) -	6.1	-6.5		-5.0		-4.7	
Probability of compliance		ç	9.8%	1	00.0%	99	.5%	99.2%	6	

7 CONCLUSIONS

It has been demonstrated that the Monte-Carlo modified Evolutionary Algorithm is a very powerful method for the purposes of maximising the number of noise sources active at a site with numerous noise sources. With variable noise emissions and variable sound propagation from the sources to the receivers, the Monte-Carlo modified Evolutionary Algorithm is able to maximise the number of noise sources that can be simultaneously active on site while ensuring that the noise level criteria is achieved for a specified minimum percentage of time at all receivers.



8 REMARKS

In practice, it is usually not possible to allow all noise sources on site to be shut down due to noise reasons, as there will be some noise sources that are critical for operation, for example the main excavator in a truck-andshovel mining team cannot be shut down because then the trucks would have nothing to haul. In those cases, the critical items can be excluded from the optimisation algorithm by fixing their status to "ON".

When the Evolutionary Algorithm is used to optimise situations where the input variables incorporate uncertainty, the computation time is considerably longer (approximately 3 to 4 times as long) than if the variables were defined with no uncertainty because the algorithm needs to run multiple times.

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