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A Genetic Algorithm Approach to the Selection of Engineering Controls for Optimal Noise Reduction

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ABSTRACT: The selection of engineering controls for workplace noise reduction can be formulated as a *zero-one* nonlinear programming problem which is *NP* hard. Given a noise control budget and a set of worker locations, the problem objective is to find a combination of feasible engineering controls to minimize a maximum daily noise load. A genetic algorithm (GA) is developed to find an optimal (or near-optimal) noise control solution. Suitable GA parameters and operations are determined from a computational experiment. GA is found to be efficient in solving engineering noise control problems irrespective of the problem size.

KEYWORDS: Genetic algorithm, noise reduction, optimization, knapsack problem, capital budgeting.

INTRODUCTION

Noise-induced hearing loss is one of the most common occupational diseases and the second most self-reported occupational illness or injury. In British Columbia, Canada, the workers' compensation board paid $18 million in permanent disability awards during 1994-1998 to 3,207 workers suffering hearing loss. An additional $36 million was paid out for hearing aids.[1] According to the National Institute for Occupational Safety and Health (NIOSH), USA; approximately 30 million U.S. workers are currently exposed to noise hazard on the job and an additional 9 million U.S. workers risk getting hearing loss.[1] A major cause of occupational hearing loss is a repetitive exposure to excessive noise levels. Since hearing loss is hardly cured, the prevention of such exposure is the best approach. When workers are exposed to a noise condition exceeding a permissible level, they are at high risk of hearing loss and a noise control program must be conducted to reduce their noise exposures. To prevent workplace noise hazard, safety practitioners are strongly recommended to apply appropriate engineering controls as the first resort.[2]

Implementation of engineering controls is the most effective approach for the noise control program. This approach involves the noise reduction at noise sources and the blocking of noise transmission between noise sources and workers. Examples of engineering controls include proper acoustical design of machinery, enclosure of noisy machine (if practical), modification of the existing machine design, and use of sound barrier and sound absorption along the transmission path. Details of engineering controls can be found in a number of publications.[3-8] More specifically, topics such as a development of quieter machines, noise reduction methods, noise absorption materials, and process change for noise reduction have been discussed in the literature.[9-18]

Engineering approach is the best approach for noise control problems because it solves the problem at its root cause. Nevertheless, it usually is the most expensive approach. Engineering controls differ in the cost and noise reduction capability. Sutton[19] presented a procedure to identify possible engineering methods of noise reduction and to select the best method using a cost/benefit analysis. The cost/benefit approach is a simple approach but it does not guarantee an optimal solution. Briefly, a cost/benefit ratio, which is a ratio of the noise reduction cost to the amount of noise that is reduced at the noise source, is developed for each noise control technique. The noise control technique having a lowest cost/benefit ratio will then be selected. This selection procedure, however, has limited application since it considers only engineering controls at the noise sources. Nor does it consider the noise control budget.

The selection of engineering controls to reduce noise levels at worker locations can be formulated as a *zero-one* nonlinear programming problem. This problem is a variant of the knapsack problem which is *NP*-hard. Pisinger[20] provided an overview of recent exact solution approaches and showed the difficulty in solving the knapsack problem. A review on the nonlinear knapsack problem was given by Bretthauer and Shetty.[21] They discussed algorithms and applications of the nonlinear knapsack problem.

Among various meta-heuristic techniques, genetic algorithm (GA) has been well adopted by researchers to find good solutions for global and hard-solving optimization problems. GA is widely used to solve linear/nonlinear *zero-one* programming problems as well as linear/nonlinear integer programming problems. Yokata et al.[22,23] formulated an optimal design problem of systems reliability as the *zero-one* nonlinear programming problem with interval coefficients and solved it using GA. GA is also used to determine solutions for various optimization problems in recent research studies.[24-33] GA has been applied to solve manufacturing problems such as scheduling problems in flexible manufacturing systems[34], sequencing problems in mixed model assembly lines[35] and in non-manufacturing problems such as fair bandwidth allocation[36] and multi-objective land use planning problems.[37]

This paper discusses a GA approach to determine a set of feasible engineering controls for optimal noise reduction. The problem objective is to minimize a maximum daily noise load at any worker location without exceeding the given noise control budget. The paper is organized as follows. Initially, we present relevant mathematical equations for computing a daily noise load and an optimization model for selecting feasible engineering controls. Next, we develop GA for the engineering noise control problem (ENCP) and explain how the suitable settings of GA parameters are determined. We also discuss the effectiveness of GA by comparing GA solutions with those from an optimization approach. Lastly, we demonstrate how GA is applied to solve the ENCP.

Engineering Noise Control Problem

Problem description

Generally, an industrial facility has several primary noise sources (manufacturing machines) and secondary noise sources (air compressors, industrial fans, industrial pumps, and cooling towers). The noise generated from these sources is transmitted to workers who are present in that facility. In most countries, a safety law requires that workers do not receive a daily noise exposure beyond the permissible level. For example, the permissible noise exposure level in the U.S. is set at 90 dB*A* for an 8-hour workday.[2] If there is any worker whose daily noise exposure exceeds this limit, an effective noise control program needs to be implemented. The engineering approach for noise control is recommended as the first line of defense owing to its high effectiveness.

Typical engineering controls include reducing noise levels at the noise sources (or controlling at the source) and blocking the noise transmission path (or controlling along the path). To reduce the generated noise at any noise source, there usually are several techniques that can be applied. An important result of this noise control is that noise levels at all worker locations are attenuated, but attenuation levels differ depending on distances between the noise source and individual worker locations. Similarly, there usually are several techniques for controlling noise along its path (e.g., putting up physical barriers or curtains), and with varying noise attenuation capabilities. Only noise levels at the worker locations in which the direct paths between the noise source and the locations are blocked will be reduced. Comparing between controlling at the source and controlling along the transmission path, the former is more effective than the latter, but it is also more expensive to implement. With the given noise control budget, safety practitioners must decide on a combination of engineering noise control(s) to yield a maximum noise attenuation. More specifically, if controlling at the source is being considered, it is necessary to determine which noise source(s) is/are to be controlled and with which noise control technique(s). In case of blocking along the path, the type of barrier/curtain and its location will depend on the intended worker locations.

Estimation of Combined Noise Level and Daily Noise Exposure

When there are multiple noise sources in the facility, the combined noise level at worker location j, $\overline{L}_j$ (dB*A*), can be computed. Letting L_{ab} be ambient noise level (dB*A*), L_t be noise level generated by noise source t (dB*A*, measured at 1-m distance), q be number of noise sources, n be number of worker locations, and d_{jt} be Euclidean distance between worker location j and noise source t, we have

$$\overline{L}_j = 10\log\left[10^{\left(\frac{L_{ab}-120}{10}\right)} + \sum_{t=1}^{q}\frac{10^{\left(\frac{L_t-120}{10}\right)}}{d_{jt}^2}\right] + 120$$

$$j = 1, \ldots, n \qquad (1)$$

If a worker is to be assigned to worker location j throughout an entire workday, his/her daily noise exposure (or 8-hour time-weighted average noise level, 8-hr TWA) will be equal to $\overline{L}_j$. In several countries, the permissible daily noise exposure is set at 90 dB*A*. For the sake of mathematical modeling, we define a unitless variable called daily noise load l to represent the daily noise exposure. The daily noise load l can be computed from

$$l = 2^{\left(\frac{\bar{L}_j - 90}{5}\right)} \quad (2)$$

Note that a permissible daily noise load l_p is equal to one.

From Eq. (1), it is seen that if an amount of generated noise at noise source t, L_t, is reduced, all $\bar{L}_j$'s will be reduced as well. However, noise attenuation at any worker location is nonlinear and dependent of the amount of noise reduction and the distance between the concerned worker location and noise source. As such, the noise reduction at noise sources having high noise levels may not yield a good solution if those sources are located far from the worker location under consideration.

MATHEMATICAL FORMULATION

The definition of the binary knapsack problem can be given as follows.[38] Suppose that a hiker has to fill up his/her knapsack by selecting from among various possible objects those of which will give the maximum comfort. Letting c be size of a knapsack, n be number of objects, w_j be size of object j, p_j be measure of comfort given by object j, x_j be (0, 1) binary variable (where $x_j = 1$ if object j is selected, and $x_j = 0$ otherwise), the knapsack problem can be mathematically formulated as shown below.

$$\text{Maximize} \quad \sum_{j=1}^{n} p_j x_j \quad (3)$$

$$\text{subject to} \quad \sum_{j=1}^{n} w_j x_j \le c \quad (4)$$

$$x_j = \{0, 1\} \qquad j = 1, \ldots, n \quad (5)$$

The knapsack problem is one of the most intensively studied discrete programming problems. The reason for such interest basically derives from three facts: (1) it can be viewed as the simplest *integer linear programming* problem; (2) it appears as a sub-problem in many more complex problems; and (3) it may represent a great many practical situations.[38]

The engineering noise control problem (ENCP) is a variant of the binary knapsack problem. Given the limited budget, a set of engineering controls are to be selected for implementation to achieve the maximum noise attenuation without exceeding the budget.

Objective Function

The objective of the ENCP is to minimize the maximum daily noise load at any worker location, $l_{\max}$.

$$\text{Minimize} \quad l_{\max} \quad (6)$$

Constraints

The ENCP requires three sets of constraint: (1) budget constraint; (2) noise load constraint; and (3) binary variable constraint.

A total noise control cost consists of cost of controlling noise at the source and cost of blocking the noise transmission by a barrier. Letting ys_{tu} be (0, 1) binary variable such that $ys_{tu} = 1$ if controlling at noise source t using engineering control method u is applied, and $ys_{tu} = 0$ otherwise; cs_{tu} be cost of controlling at noise source t using engineering control method u; q be number of noise sources; r_t be number of engineering control methods of controlling at noise source t, we have

Cost of controlling noise at the source

$$= \sum_{t=1}^{q} \sum_{u=1}^{r_t} \left(cs_{tu} \times ys_{tu} \right) \quad (7)$$

Cost of blocking the noise transmission by a barrier can be determined in a similar fashion. Letting yb_v be (0, 1) binary variable such that $yb_v = 1$ if blocking the noise transmission path using barrier v is applied, and $yb_v = 0$ otherwise; cb_v be cost of installing barrier v; s be number of barriers, we obtain

Cost of blocking the noise transmission path

$$= \sum_{v=1}^{s} \left(cb_v \times yb_v \right) \quad (8)$$

Since the sum of both costs must not exceed the given noise control budget EB, the budget constraint can be formulated as

$$\left[\sum_{t=1}^{q} \sum_{u=1}^{r_t} \left(cs_{tu} \times ys_{tu} \right) + \sum_{v=1}^{s} \left(cb_v \times yb_v \right) \right] \le EB \quad (9)$$

After applying the selected noise control at the source, the reduced noise level at noise source t, L'_t, can be computed from

$$L'_t = L_t - \sum_{u=1}^{r_t} \left(NRs_{tu} \times ys_{tu} \right) \quad t = 1, \ldots, q \quad (10)$$

where NRs_{tu} is the amount of noise reduction (dBA) at noise source t after applying noise control method u.

As a result of noise control, the combined noise levels at all (if controlling at the noise source has been applied) or some (if blocking the noise transmission path has been applied) worker locations will be reduced. Letting NRb_{jv} be amount of noise reduction (dBA) at worker location j after installing barrier v, the combined noise level at that location then becomes

$$\bar{L}_j = 10\log\left[10^{\left(\frac{L_{ab}-120}{10}\right)} + \sum_{t=1}^{q}\frac{10^{\left(\frac{L'_t-120}{10}\right)}}{d_{jt}^2}\right]+120$$

$$-\sum_{v=1}^{s}\left(NRb_{jv}\times yb_v\right) \qquad j=1,\ldots,n \qquad (11)$$

From Eq. (11), the daily noise load constraint can be written as

$$2^{\left(\frac{\bar{L}_j-90}{5}\right)} \le l_{\max} \qquad (12)$$

Finally, the binary variable constraint is defined for ys_{tu} and yb_v.

$$ys_{tu}, yb_v = (0, 1)$$

$$t=1,\ldots,q;\ u=1,\ldots,r_t;\ v=1,\ldots,s \qquad (13)$$

Thus, the ENCP model will have the objective function (Eq. (6)) and constraints ((9) – (13)) as summarized below.

Minimize $\quad l_{\max}$

subject to

$$\left[\sum_{t=1}^{q}\sum_{u=1}^{r_t}\left(cs_{tu}\times ys_{tu}\right)+\sum_{v=1}^{s}\left(cb_v\times yb_v\right)\right] \le EB$$

$$L'_t = L_t - \sum_{u=1}^{r_t} NRs_{tu}\times ys_{tu} \qquad t=1,\ldots,q$$

$$\bar{L}_j = 10\log\left[10^{\left(\frac{L_{ab}-120}{10}\right)} + \sum_{t=1}^{q}\frac{10^{\left(\frac{L'_t-120}{10}\right)}}{d_{jt}^2}\right]+120$$

$$-\sum_{v=1}^{s} NRb_{jv}\times yb_v \qquad j=1,\ldots,n$$

$$2^{\left(\frac{\bar{L}_j-90}{5}\right)} \le l_{\max}$$

$$ys_{tu}, yb_v = \{0,1\} \quad t=1,\ldots,q;\ u=1,\ldots,r_t;\ v=1,\ldots,s$$

As one can see, the ENCP is a *minimax* optimization problem with nonlinear constraints. Also, since it is the *zero-one* nonlinear programming problem, it cannot be solved to optimality when the problem size is large. To yield the optimal or near-optimal solution, we develop the genetic algorithm (GA) for the ENCP.

Genetic Algorithm Approach to ENCP

The genetic algorithm (GA) approach is employed to optimally select feasible engineering controls for the maximum noise attenuation without exceeding the noise control budget. Detailed discussion on GAs can be found in Holland[39], Michalewicz[40], and Gen and Cheng.[41, 42] In this section, we explain GA that is specifically developed for the ENCP. Topics covered include: (1) GA procedure, (2) chromosome coding and initial population, (3) crossover, (4) mutation, (5) fitness and evaluation function definitions, (6) repairing procedures (7) selection techniques, and (8) termination rules.

GA Procedure

GA procedure is illustrated in Fig. 1. Parameters required for the proposed GA include crossover probability *Pc*, mutation probability *Pm*, population size *Popsize*, and maximum generation *Maxgen*. Firstly, set an initial generation as *gen* = 0. If a repair procedure is required, a repair rate must also be specified. Next, binary string v_k (k = 1, 2,…, *Popsize*) is created. Each string (chromosome) represents a feasible solution for the ENCP. Essential GA operations including crossover, mutation, and selection are part of the evolution process. According to the survival-of-the-fittest rule, an evaluation function (to determine a fitness value) must be evaluated prior to the selection. The best chromosome is registered after the selection process. Then, update the *gen* value (*gen* = *gen* +1). Repeat GA procedure until *gen* = *Max_gen*. In addition, if the repairing procedure is employed, it will be executed after the crossover and mutation operations.

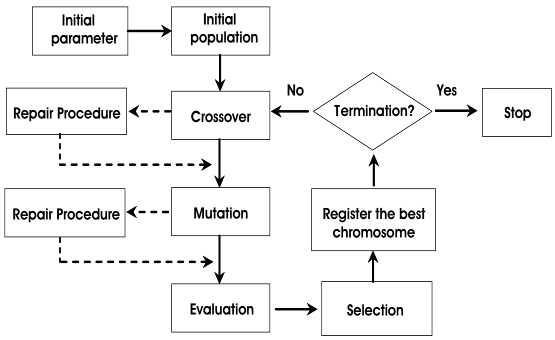


Fig 1. The genetic algorithm procedure.

Chromosome Coding and Initial Population

Binary encoding is employed in the proposed GA to create chromosomes because the decision variables of the ENCP are zero or one. The length of chromosome is equal to the number of engineering controls that are feasible for the problem being considered, $s+\sum_{t=1}^{q} r_t$. An initial population is randomly generated. Note that the number of chromosomes in the (initial and subsequent) populations is constant and is denoted by *Popsize*.

Crossover

Crossover is a GA operation which attempts to generate two new chromosomes that may be stronger than their parents. Two parent chromosomes are randomly selected from the current population for mating. Two new chromosomes, called offspring, will be created by swapping some parts of the parent chromosomes. Crossover probability *Pc* indicates the number of chromosome pairs that will be involved in the crossover operation. For our GA procedure, two crossover techniques are considered: (1) single-point crossover, and (2) two-point crossover.

Single-point Crossover

Single-point crossover is a simple technique that combines two parent chromosomes to generate two offspring. To achieve this, a random cut-point is chose and two new offspring are generated by swapping the left-hand-side segments after the cut-point of the selected parents. Fig. 2 (a) illustrates the single-point crossover technique.

(a)

```
011|0110010  Parents
101|0100001

101|0110010  Offspring
011|0100001
```

(b)

```
011|011|0010  Parents
101|010|0001

011|010|0010  Offspring
101|011|0001
```

Fig 2. (a) Single-point crossover, and (b) Two-point crossover

Two-point Crossover

This crossover technique combines two parent chromosomes by choosing two random cut-points. Unlike the single-point crossover, the middle segments between both cut-points of the two parents are swapped to create two offspring as illustrated in Fig. 2 (b).

Mutation

Mutation is a GA operation which makes random alterations to various chromosomes. Random mutation changes a small number of bits in chromosomes depending on mutation probability *Pm* that indicates the number of mutated bits. A single-point mutation, which is used in this paper, alters a value "1" to "0," and vice versa. Letting *mut_no* and *chro_l* denote number of mutated bits and length of chromosome, respectively, then *mut_ no* can be computed as follows.

$$mut\_no = Pm \times chro\_l \times popsize \tag{14}$$

The mutation operation is illustrated in Fig 3.

```
↓     ↓ ↓
0110110010  Parents
0100110111  Offspring
```

Fig 3. Mutation operation

Fitness and Evaluation Function Definitions

An evaluation function is used to evaluate the fitness of chromosomes in each generation. The chromosomes having high evaluation values will potentially be selected for the next generation. To obtain the evaluation function, a fitness function and a penalty coefficient have to be defined. Details of these topics can be found in Michalewicz et al.[43] and Gen and Cheng.[41, 42]

Fitness Function

The fitness function is problem specific. For the ECNP, a fitness value is defined as the maximum daily noise load l_{max}. When comparing between two chromosomes, since the problem objective is to minimize l_{max}, a stronger chromosome is the chromosome that has a lower l_{max} than the other one. The fitness function $f_k(v_k)$ can be written as

$$f_k(v_k) = l_{max} \tag{15}$$

Penalty Function

Since the ENCP has an upper bounded constraint which is the engineering control budget *EB*, a penalty term is added to the fitness function so that the chromosome that falls in infeasible space will have a lesser chance to be selected for the next generation. A penalty coefficient p_k, where $k = 1,\ldots,$ *Popsize*, is proportional to the amount of extra budget that can be determined from the following function.

$$p_k = \begin{cases} 0, & \text{if budget constraint is satisfied} \\ \theta\left(\sum_{t=1}^{q}\sum_{u=1}^{r_t}\left(cs_{tu} \times ys_{tu}\right) + \sum_{v=1}^{s}\left(cb_v \times yb_v\right)\right) \\ \text{-}EB, & \text{otherwise} \end{cases} \tag{16}$$

where q is a large positive value.

Evaluation Function

From Eqs. (15) and (16), the evaluation function $eval(v_k)$, where $k = 1,\ldots, Popsize$, can be expressed as

$$eval(v_k) = \frac{1}{f_k(v_k) + p_k}$$

$$k = 1, 2, \ldots, Popsize \qquad (17)$$

Repair Procedures

After performing the crossover and mutation operations, new chromosomes may be infeasible since the total cost exceeds the noise control budget. They have to be repaired before they can be considered for the next generation. Further discussion on the chromosome repairing issue can be found in Michalewicz et al.[43] The number of infeasible offspring to be repaired must not be greater than the value computed from [repair rate ´ *Popsize*]. Here, we consider two repair procedures, each of which can be employed to repair any infeasible chromosomes.

Random Repair Procedure

This technique randomly changes bits that have a value "1" to "0." This random change is repeated until the budget constraint is satisfied.

Ordered Repair Procedure

The amount of noise generated from a noise source reaching a worker location depends on how far the location is from the noise source. Let us define a noise impact of the noise source as a sum of intensities (in W) of noise from that noise source measured at all worker locations. Thus, the noise impact of noise source t, T_t, can be computed from

$$T_t = \left[\sum_{j=1}^{n} \frac{10^{\left(\frac{L_t - 120}{10}\right)}}{d_{jt}^2} \right] \qquad (18)$$

There are 21 steps required to complete the ordered repair procedure.

Given

- bn_i = value of bit number i
- i^* = selected bit number
- j^* = selected worker location number
- *rank_no* = ranking number
- *sum_bit* = sum of bit values of bit number ranging between L and U
- t^* = selected noise source number

Step 1: Rank T_t in ascending order.
Step 2: Determine *rank_no* of all noise sources from the order of T_t obtained in Step 1.
Step 3: Set $e = 1$.
Step 4: Select t^* having *rank_no* = e.
Step 5 : Set $L = \sum_{t=1}^{t^*-1} r_t + 1$ and $U = \sum_{t=1}^{t^*} r_t$.
Step 6 : Calculate *sum_bit* = $\sum_{i=L}^{U} bn_i$. If *sum_bit* is greater than or equal to 1, then go to Step 7. Otherwise, go to Step 10.
Step 7 : Randomly select i^* where $L \le i^* \le U$.
Step 8 : If bn_{i^*} = "1," then change it to "0" and go to Step 9. Otherwise, return to Step 7.
Step 9 : If $\left[\sum_{t=1}^{q} \sum_{u=1}^{r_t} \left(cs_{tu} \times ys_{tu}\right) + \sum_{v=1}^{s} \left(cb_v \times yb_v\right) \right] > EB$ then go to Step 10. Otherwise, stop repairing.
Step 10: If $e < q$, then set $e = e + 1$ and go to Step 4. Otherwise, go to Step 11.
Step 11: Calculate $\overline{L}_j$ when no engineering control is implemented and rank $\overline{L}_j$ in ascending order.
Step 12: Determine *rank_no* of all worker locations from the order of $\overline{L}_j$ in Step 11.
Step 13: Set $e = 1$.
Step 14: Set $L = \sum_{t=1}^{q} r_t + 1$ and $U = \sum_{t=1}^{q} r_t + s$.
Step 15: Select j^* having *rank_no* = e.
Step 16: Calculate *sum_bit* = $\sum_{i=L}^{U} bn_i$. If *sum_bit* is greater than or equal to 1, then go to Step 17. Otherwise, stop repairing.
Step 17: Set $k = 1$.
Step 18: If $NRb_{j^*,v=k} > 0$ and bn_i (where $i = L + k - 1$) = "1," then let bn_i = "0." Otherwise, go to Step 19.
Step 19: If $\left[\sum_{t=1}^{q} \sum_{u=1}^{r_t} \left(cs_{tu} \times ys_{tu}\right) + \sum_{v=1}^{s} \left(cb_v \times yb_v\right) \right] > EB$ then go to Step 20. Otherwise, stop repairing.
Step 20: If $k < s$, then set $k = k + 1$ and return to Step 18. Otherwise, go to Step 21.
Step 21: If $e < n$, then set $e = e + 1$ and return to Step 15. Otherwise, stop repairing.

Selection Techniques

For the selection procedure, two basic topics are discussed: (1) sampling space, and (2) sampling mechanism. Various methods for selecting chromosomes are later examined in the computational experiment.

Sampling Space

Two types of sampling space are investigated in this paper. They are: (1) regular sampling space, and (2) enlarged sampling space.

Regular Sampling Space

The size of regular sampling space is always equal to *Popsize*. This is because newly generated offspring will replace their parents after their birth. Originally, this procedure is called *generational replacement*.

Enlarged Sampling Space

Both parents and offspring have been retained in the sampling space, called enlarged sampling space. Therefore, the size of sampling space is equal to *Popsize* + (*cross_pair* × 2) + *mut_no*. In this method, parents and offspring have their chances to be selected for the new generation depending upon their fitness values.

Sampling Mechanism

The sampling mechanism involves how to select chromosomes from the sampling space for the new generation. Two sampling mechanism techniques are considered.

Roulette Wheel Selection with Elitist Selection

The roulette wheel selection technique is an elitist approach in which the best chromosome has a highest probability to be selected for the new generation. The basic roulette wheel is a stochastic sampling with replacement. The higher the evaluation function value a chromosome has, the greater potential it will be selected as a member of the new generation. The new generation has the same population size as the previous one. With the elitist selection, the best chromosome is firstly selected for inclusion in the new generation.

Ranking Selection

The evaluation function values of all chromosomes in the sampling space are firstly calculated. Then, they are sorted and listed in descending order (i.e., from the best to the worst). The number of chromosomes to be selected for inclusion in the new generation is *Popsize*. This approach prohibits duplicate chromosomes from passing onto the new generation.

Termination Rules

Since GA is an iterative approach, GA procedure is terminated when the number of iterations has reached the maximum generation denoted by *Max_gen*.

Analysis of GA Parameters

When applying GA, it is known that the quality of the solution and the effectiveness of GA are likely to be influenced by the parameter settings. A computational experiment is conducted to investigate effects of the crossover probability *Pc*, mutation probability *Pm*, population size *Popsize*, and maximum generation *Max_gen* on l_{max}.

The experiment is designed as a full-factorial experiment with four factors (i.e., *Pc*, *Pm*, *Popsize*, and *Max_gen*) and three replicates. A dependent variable in this experiment is the maximum daily noise load l_{max}. The number of levels (treatments) and the settings of each factor are shown in Table 1. There are 360 runs in the experiment. Two problem sizes (determined by the numbers of noise sources and worker locations) are investigated: (1) 8 noise sources (q = 8) and 8 worker locations (n = 8), and (2) 20 noise sources (q = 20) and 20 worker locations (n = 20). The results of the

Table 1. Factors and levels of the full-factorial experiment

Factors	Number of Levels	Settings
Pc	5	0.1, 0.2, 0.3, 0.4, 0.5
Pm	6	0.05, 0.10, 0.15, 0.20, 0.25, 0.30
Popsize	2	50, 100
Max_gen	2	100, 10000

Table 2. ANOVA table for the 8 x 8 problem size

Source of Variation	Degrees of Freedom	Sum of Squares	Mean Square	F_0	*P-value*
Pc	4	0.0000012	0.0000003	3.45	0.009
Pm	5	0.0000006	0.0000001	1.45	0.205
Popsize	1	0.0000023	0.0000023	27.35	0.000
Max_gen	1	0.0000047	0.0000047	54.84	0.000
Pc x *Pm*	20	0.0000024	0.0000001	1.42	0.112
Pc x *Popsize*	4	0.0000002	0.0000001	0.63	0.640
Pc x *Max_gen*	4	0.0000012	0.0000003	3.45	0.009
Pm x *Popsize*	5	0.0000004	0.0000001	0.95	0.449
Pm × *Max_gen*	5	0.0000006	0.0000001	1.45	0.205
Popsize × *Max_gen*	1	0.0000023	0.0000023	27.35	0.000
Error	309	0.0000262	0.0000001		
Total	359	0.0000421			

Table 3. ANOVA table for the 20 x 20 problem size

Source of Variation	Degrees of Freedom	Sum of Squares	Mean Square	F_0	*P-value*
Pc	4	0.0007400	0.0001850	5.82	0.000
Pm	5	0.0003666	0.0000733	2.31	0.045
Popsize	1	0.0006142	0.0006142	19.31	0.000
Max_gen	1	0.0466907	0.0466907	1468.05	0.000
Pc x *Pm*	20	0.0005300	0.0000265	0.83	0.673
Pc x *Popsize*	4	0.0003666	0.0000917	2.88	0.023
Pc x *Max_gen*	4	0.0001372	0.0000343	1.08	0.367
Pm x *Popsize*	5	0.0000562	0.0000112	0.35	0.880
Pm x *Max_gen*	5	0.0000178	0.0000036	0.11	0.990
Popsize × *Max_gen*	1	0.0000899	0.0000899	2.83	0.094
Error	309	0.0098276	0.0000318		
Total	359	0.0594368			

analysis of variance (ANOVA) of the 8 x 8 and 20 x 20 problem sizes are shown in Tables 2 and 3, respectively.

From Tables 2 and 3, it is found that *Pc*, *Popsize* and *Max_gen* have significant effects on l_{max} in both problem sizes. *Pm* only has a significant effect on l_{max} in the 20 20 problem. Based on the results from the statistical analysis, we set *Pc* = 0.5, *Pm* = 0.05, and *Popsize* = 50. *Max_gen*, however, will vary with the problem size.

Analysis of GA Operations

In this section, the effects of sampling space, selection method, crossover and mutation techniques, and repair procedure are investigated in another computational experiment. As shown in Table 4, six treatments (P1, P2, …, P6) with different combinations of sampling space, selection method, crossover and mutation techniques, and repair procedure are described. For each treatment, nine problem sizes as indicated by the numbers of noise sources and worker locations (4 x 4, 6 x 6, 8 x 8, 10 x 10, 15 x 15, 20 x 20, 30 x 30, 40 x 40, and 50 x 50) are examined. For each problem size, five sub-problems (S-1 to S-5) are tested. All sub-problems are randomly generated using L_t, r_t, and *s* ranging between 85 - 105 dB*A*, 0 - 3 methods, and 2 - 16 methods, respectively.

Table 5 shows the maximum generations for the nine problem sizes in the experiment. The experiment is repeated with 10 replicates for each sub-problem. Therefore, the experiment consists of 450 experimental runs (9 problem sizes ´ 5 sub-problems ´ 10 replicates). GA procedure is implemented in VBA (Microsoft Excel) and is run on Pentium IV, 2.80 GHz, and 512 MB RAM personal computers.

An average l_{max} from the 10 replicates is used as a quantitative measure to represent GA solution and to compare among different solutions. A plot of the average l_{max} versus the number of generations of the 20´20 problem size (sub-problem: S-2) is illustrated in Fig. 4. It is seen that the average l_{max} converges quickly to the best solution within the first two hundred generations, after which it levels off. Fig. 5(a) and Fig. 5(b) show changes in the average l_{max} and average CPU time, respectively, with respect to the problem size for

Table 4. GA operations for the six treatments

GA Operation	Treatment P1	P2	P3	P4	P5	P6
Sampling Space	Regular	Enlarged	Enlarged	Enlarged	Enlarged	Enlarged
Selection Method	Roulette Wheel	Roulette Wheel	Roulette Wheel	Ranking	Roulette Wheel	Roulette Wheel
Crossover	Single-point Crossover					
Mutation	Single-point Mutation					
Repair Procedure	None	None	None	None	Random[a]	Ordered[a]

[a]Repair rate = 0.20

Table 5. Maximum number of generations for the nine problem sizes

Problem size	4 x 4	6 x 6	8 x 8	10 x 10	15 x 15	20 x 20	30 x 30	40 x 40	50 x 50
Max_gen	2,000	2,000	2,000	4,000	4,000	7,000	8,000	8,000	8,000

all six treatments and for the optimization approach. An optimization software tool called LINGO is used to solve the ENCP to optimality. Its computation time limit is set at 50,000 seconds. From Fig. 5(a), it is seen that combinations P2, P3, P5, and P6 are superior to the others due to their lower average l_{max}'s. For the two largest problem sizes (40 x 40 and 50 x 50), the average l_{max} from combination P6 is found to be the lowest.

In terms of computation time, the average CPU time increases with the problem size in all six treatments (see Fig. 5(b)). Furthermore, the increases are found to be progressive when the problem size is 15 x 15 or larger. When LINGO is utilized, the optimal solution could be obtained only when the problem size is small (not larger than 15 x 15). Among the six treatments, combination P1 requires the least amount of CPU time to yield the best solution, while combinations P2, P3, P4, and P6 require relatively equal computation times.

Since our emphasis is on the quality of the solution (as measured by how low the average l_{max} is), GA operations employed in combination P6 are chosen as those to be used in GA approach to the ENCP. Specifically, enlarged sampling space, roulette wheel selection, single-point crossover, single-point mutation, and ordered repair procedure are employed, with P_c = 0.5, P_m = 0.5, and *Popsize* = 50.

Next, we perform a statistical analysis to study differences in the average l_{max} between solutions from the GA approach (i.e., combination P6) and the optimization approach (i.e., LINGO). The results (% deviation) are shown in Table 6. When the problem sizes are small (e.g., 4 x 4, 6 x 6, and 8 x 8), GA is able to yield the optimal solutions in all sub-problems. For the next two larger problem sizes (10 x 10 and 15 x 15), GA is effective in about 50% of the sub-problems solved. Nevertheless, at its worst performance, the solution from GA is still only 0.29% greater than the optimal solution.

Table 6. % deviation of average l_{max} $[(l_{max}(P6) - l_{max}(LINGO))/l_{max}(LINGO)]$

Problem Size	Sub-problem				
	S-1	S-2	S-3	S-4	S-5
4 x 4	0.00	0.00	0.00	0.00	0.00
6 x 6	0.00	0.00	0.00	0.00	0.00
8 x 8	0.00	0.00	0.00	0.00	0.00
10 x 10	0.00	0.05	0.00	0.00	0.08
15 x 15	0.04	0.00	0.29	0.17	0.00
20 x 20	0.70	-4.31[a]	-15.53[a]	-3.07[a]	-13.17[a]
30 x 30	-0.52[a]	-0.87[a]	-17.87[a]	-9.20[a]	-1.50[a]
40 x 40	2.14	*	0.00	0.03	*
50 x 50	-18.20[a]	*	*	*	*

*LINGO cannot find any feasible solution within 50,000 seconds.
[a]LINGO can find only the feasible solution.

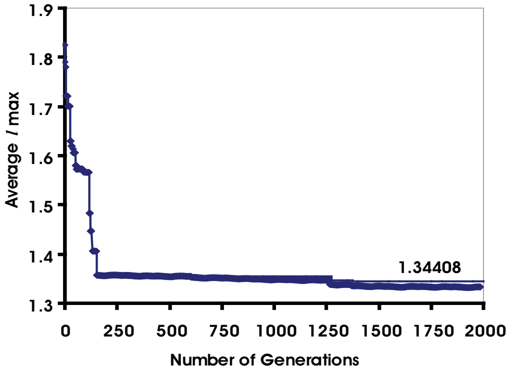
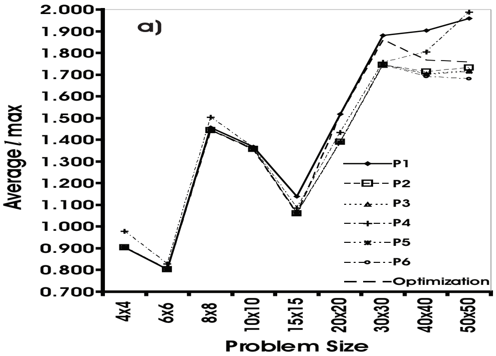


Fig 4. Plot of number of generations vs. average l_{max} for the 20×20 problem size (sub-problem: S-2)



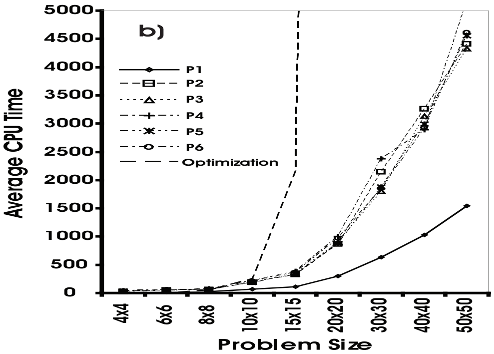


Fig 5. Plots of (a) problem size vs. average l_{max}, and (b) problem size vs. average CPU time

For the problem sizes greater than 15 x 15, LINGO is able to solve four (out of 20) problems to optimality. In some problems, LINGO can find only feasible solutions within 50,000 seconds. There are six problems (with the problem sizes 40 x 40 and 50 x 50) for which LINGO cannot obtain feasible solutions within 50,000 seconds. When GA is used, a maximum % deviation from the optimal solutions is found to be 2.14% (at the 40 x 40 problem). In those problems for which LINGO can find feasible solutions, the solutions from GA are superior to those from LINGO.

Thus, it is evident that GA approach is an effective means for solving the ENCP. GA solution is optimal when the problem size is small. For larger problems for which the optimization approach fails to find the optimal solutions, GA can yield the solutions with small deviations from the best solutions obtained by the optimization software tool used. Additionally, the computation time when using GA is also short, making it a very practical means for solving the ENCP.

NUMERICAL EXAMPLE

Let us consider an industrial facility with eight machines (q = 8) and eight worker locations (n = 8). Location coordinates of the eight machines and their noise levels (measured at 1-m distance) are shown in Table 7. At present, there are eight workers being assigned to eight different worker locations, and each worker must be at the same worker location for 8 hours. Location coordinates of the eight worker locations are also shown in Table 7. Ambient noise level in this facility is assumed to be 70 dB*A*. When no engineering noise control is implemented, 8-hour TWAs at the eight worker locations are as shown in Table 8. From Eq. (2), the maximum daily noise load l_{max} is found to be 2.2038 (at worker location WL5).

Noise control data for this example is as shown below.

- Noise control budget EB = 20,000 baht.
- There are two methods for blocking the noise transmission path. When applied, noise reduction occurs at worker locations WL5 and WL6. The amount of noise reduction is 7 dB*A* at each location. The barrier cost is 3,800 baht, and is the same for both methods.
- There are two methods for controlling noise at the machines. Noise reduction data (in dB*A*) at the eight machines when each method is utilized (wherever applicable) and noise control costs (in baht) are as follows:

$$[NRs_{tu}] = \begin{bmatrix} 10 & - \\ 8 & - \\ 8 & - \\ 10 & - \\ 8 & 12 \\ 8 & 12 \\ 8 & 12 \\ 8 & 12 \end{bmatrix}, \quad [cs_{tu}] = \begin{bmatrix} 5,000 & - \\ 3,500 & - \\ 3,500 & - \\ 5,000 & - \\ 4,500 & 5,500 \\ 4,500 & 5,500 \\ 4,500 & 5,500 \\ 4,500 & 5,500 \end{bmatrix}$$

GA is applied to find feasible engineering controls that will minimize the maximum daily noise load such that the total noise control cost does not exceed 20,000 baht. GA parameters are Pc = 0.5, Pm = 0.05, *Popsize* = 50, and *Max_gen* = 2,000 generations. Enlarged sampling space, roulette wheel selection with elitist selection, single-point crossover, single-point mutation, and ordered repair procedure are selected as GA operations.

A noise control solution recommended by GA requires the following engineering controls:

- Reducing noise at machine M5 using engineering control method 1
- Reducing noise at machine M6 using engineering control method 1
- Reducing noise at machine M7 using engineering control method 2
- Reducing noise at machine M8 using engineering control method 2

The total noise control cost is 20,000 baht. As a result, the *reduced* daily noise loads at the eight worker locations are 1.1173, 1.0570, 1.0570, 1.2311, 0.8351, 0.8011, 0.5987, and 0.5586, respectively. Note that the maximum daily noise load l_{max} = 1.2311 (at worker location WL4) is the minimum among those feasible solutions found by GA. Since there are several daily noise loads that exceed 1, noise hazard has not yet been eliminated. For ease of comparison, updated 8-hour TWAs at the eight worker locations after implementing the recommended engineering controls are also shown in Table 8.

Table 7. Location coordinates and noise levels of the eight machines and location coordinates of the eight worker locations

Machine	Location Coordinate (m)				Location Coordinate (m)	
	x-coordinate	*y*-coordinate	Noise Level (dB*A*)	Worker Location	*x*-coordinate	*y*-coordinate
M1	3	2	90	WL1	3	3
M2	6	2	89	WL2	6	3
M3	9	2	89	WL3	9	3
M4	12	2	91	WL4	12	3
M5	3	6	95	WL5	3	5
M6	6	6	94	WL6	6	5
M7	9	6	93	WL7	9	5
M8	12	6	93	WL8	12	5

To eliminate noise hazard, the noise control budget *EB* has to be increased. Using a trial-and-error approach, it is found when *EB* is set at 28,000 baht, the 8-hour TWAs at all worker locations do not exceed 90 dB*A* (see Table 8). The *new* recommended engineering controls are as follows:

- Reducing noise at machine M1 using engineering control method 1
- Reducing noise at machine M4 using engineering control method 1
- Reducing noise at machine M5 using engineering control method 1
- Reducing noise at machine M6 using engineering control method 1
- Reducing noise at machine M7 using engineering control method 1
- Reducing noise at machine M8 using engineering control method 1

Conclusion and Discussion

The selection of engineering controls for noise hazard prevention is examined. The ENCP is mathematically formulated as a *zero-one* nonlinear programming problem. The problem objective is to find a set of engineering noise controls without exceeding the given budget such that the maximum daily noise load is minimized. The ENCP is a variant of the knapsack problem. Genetic algorithm (GA) is developed to provide the optimal or near-optimal solution for the ENCP.

To select the appropriate GA parameters and operations, two computational experiments are carried out. The first experiment investigates the effects of GA parameters, namely, crossover probability *Pc*, mutation probability *Pm*, population size *Popsize*, and maximum generation *Max_gen* on the maximum daily noise load l_{max}. The results show that all of the above GA parameters have significant effects on l_{max}. The second experiment is intended to find the proper GA operations for solving the ENCP. Two repair procedures are developed to assist GA in enhancing the quality of the solution. Four hundred and fifty problems (9 problem sizes ´ 5 sub-problems ´ 10 replicates) are analyzed by GA. The problems are grouped into six combinations of selected GA operations (called treatments). It is found that the combination which employs enlarged sampling space, roulette wheel selection with elitist selection, single-point crossover, single-point mutation, and ordered repair procedure demonstrates the best performance (i.e., achieving the lowest average l_{max}).

When comparing between the average l_{max}'s obtained from GA and LINGO (only in small-sized problems for which LINGO can find the optimal solutions), it is seen that GA is exceptionally effective since it is able to yield the average l_{max}'s that are identical to those obtained from LINGO. When the problem size is large (e.g., 10 × 10 and 15 × 15), the average l_{max} obtained from GA is slightly greater than that from LINGO (the % deviation is found to be small). When the problem size is very large, LINGO will have difficulty finding the optimal solution within the given time limit of 50,000 seconds. Depending on the problem size, LINGO may or may not be able to find the best feasible solution within the time limit. GA, on the other hand, is able to yield the feasible solution in relatively short time irrespective of the problem size. These findings confirm the effectiveness of GA in solving the ENCP.

From the given numerical example, when the noise control budget is set at 20,000 baht, the recommended engineering controls cannot completely eliminate noise hazard since daily noise loads at some worker locations are still greater than the permissible level. By increasing the budget to 28,000 baht, the new noise control solution that is effective can now be obtained. In most real situations, the noise control budget is limited and fixed. As such, other noise control approaches should be considered. For instance, job rotation can be

Table 8. 8-hour TWAs at the eight worker locations

Worker Location	8-hour TWA (dBA)		
	Before Implementing Engineering Controls	After Implementing Engineering Controls (*EB* = 20,000 baht)	After Implementing Engineering Controls (*EB* = 28,000 baht)
WL1	92.3[a]	90.8[a]	84.8
WL2	92.1[a]	90.4[a]	90.0
WL3	92.0[a]	90.4[a]	89.9
WL4	92.6[a]	91.5[a]	84.8
WL5	95.7[a]	88.7	88.0
WL6	95.2[a]	88.4	88.1
WL7	94.4[a]	86.3	87.4
WL8	94.0[a]	85.8	86.5

[a]Exceeding the daily permissible level.

implemented to rotate workers among worker locations so as to reduce their noise hazard exposures. The use of hearing protection devices (HPDs) can be additionally enforced to reduce the amounts of perceived noise at selected worker locations. It should be noted that job rotation and the use of HPDs are not as effective as engineering noise controls, but they usually are less expensive. In practice, a combination of noise control approaches should be implemented to keep the total noise control cost from exceeding the budget and to achieve safety daily noise exposures in all workers.

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