A preliminary study to metaheuristic approach in multilayer radiation shielding optimization

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Abstract. Metaheuristics are high-level algorithmic concepts that can be used to develop heuristic optimization algorithms. One of their applications is to find optimal or near optimal solutions to combinatorial optimization problems (COPs) such as scheduling, vehicle routing, and timetabling. Combinatorial optimization deals with finding optimal combinations or permutations in a given set of problem components when exhaustive search is not feasible. A radiation shield made of several layers of different materials can be regarded as a COP. The time taken to optimize the shield may be too high when several parameters are involved such as the number of materials, the thickness of layers, and the arrangement of materials. Metaheuristics can be applied to reduce the optimization time, trading guaranteed optimal solutions for near-optimal solutions in comparably short amount of time. The application of metaheuristics for radiation shield optimization is lacking. In this paper, we present a review on the suitability of using metaheuristics in multilayer shielding design, specifically the genetic algorithm and ant colony optimization algorithm (ACO). We would also like to propose an optimization model based on the ACO method.

1. Introduction

Technology involving ionizing radiation is widely used in many fields such as medical application, manufacturing industries, and research. However, ionizing radiation is harmful to humans as it can cause biological changes in the body. The International Commission of Radiation Protection (ICRP) recommended three basic principles to control radiation exposure to the public which are justification, optimization, and dose limitation [1]. The dose can be limited using any or combination of three of the following methods of protection: minimizing the time of handling the radiation source, maximizing the distance from the source, and putting a shield between people and the source.

A shield is defined as a physical entity placed between an ionizing radiation source and an object to be protected with the aim of reducing the radiation level at the object's position [2]. It can be made of composite material, multilayer of various materials, or combinations of both. The advantage of composites is that the shielding capabilities of different materials can be merged in a single material, reducing the weight of the shield as seen in polymer composites [3]. However, they may lack uniformity, resulting in inconsistent shielding performances [4][5][6]. Non-uniform composites may also result in pin holes, pure polymer areas which radiation can penetrate through [7]. On the other hand, multilayer configuration can be advantageous in the case of mixed radiations, for example a californium-252 emitting both neutrons and gamma rays. Each of the layer can attenuate the types of
radiation which it has high macroscopic cross section or attenuation coefficient. The alternate layers of shielding can also suppress secondary radiation [8].

With the advances of technology, the requirements for the shield also increases. Different applications have different design objectives. For stationary systems, the primary consideration is cost, while for mobile applications, the total weight of the shield is more concerned. Limitations in resources would also mean that the shield design needs to be optimized and tailored to its application. A shield can be regarded as a combinatorial optimization problem (COP) when it is made up of various materials. For example, there should be an optimum weightage of fillers in a composite shield, or an optimum arrangement of layers in a multilayer shield. Metaheuristics were developed to tackle such COPs in many different fields such as economy, engineering, and industry [9]. Examples of metaheuristic algorithms are simulated annealing, tabu search, genetic algorithm (GA), and ant colony optimization (ACO). This paper focuses on GA and ACO since only GA had been implemented in optimizing composite shield. Meanwhile, we intent to propose on the optimization of a multilayer shield using ACO.

2. Combinatorial optimization problem
A combinatorial optimization deals with searching optimal combinations or permutations of available problem components. A COP is defined as \( P=(S, \Omega, f) \) in which \( S \) is a search space defined over a finite set of discrete decision variables. \( \Omega \) is a set of constraints among the variables and \( f \) is the objective function that assigns a positive cost value to each of the solutions [10].

An example of a COP is the travelling salesman problem (TSP) which was formulated in 1930 as a mathematical problem. It is represented as an undirected weighted graph, where vertices represent cities and edges represent the path connecting the cities. The goal of the optimization problem is to find the shortest total distance travelled with a condition that the salesman visits each city only once. The problem is known to be difficult computationally, but easily solvable with the use of heuristic (search) algorithms even with thousands of cities [11].

3. Metaheuristics
Optimization algorithms are classified as either complete or approximate algorithms. Optimal solutions are guaranteed when using complete algorithms, but for certain COPs that are considered NP-hard, they make take an exponential computation time. Approximate algorithms or heuristics were developed where the guarantee is sacrificed for good near-optimal solutions in a relatively reasonable computation cost. The word metaheuristics originates from meta (Greek: 'beyond, in an upper level') and heuristic (Greek:'to find'). They were also called modern heuristics. The difference between a heuristic and a metaheuristic is that the latter is problem-independent. It can be designed to solve approximately a wide range of COPs without the need of adapting deeply to each problem [9][12][13].

Genetic algorithm was popularized by John Holland in the 1970s. It was based on natural evolution and the concept of survival of the fittest. The algorithm selects the solution randomly, picks the most fit solutions, and uses them to create a new generation which is better than the previous generation. The basic GA is very general hence it can be modified to adapt to the problem at hand through implementations such as representation of solution (chromosomes), types of crossover (the recombination operator), selection strategies, and mutation operators. The pseudocode of GA is shown in figure 1(a). After recombination, individuals go through mutation where randomness was introduced into the search to prevent the optimization from getting trapped in local optima. Then, based on their fitness value, they are used for successive generations, assuring the survival of the fittest individuals [9][11].

Ant colony optimization is a technique introduced by Dorigo Marco in 1992 who took inspiration from the foraging behavior of ants. They always seek the shortest path between their colony and food sources. The unique feature in ACO is the implementation of pheromone parameter. It is associated to every solution explored by the artificial ants. Updating the pheromone value after each iteration helps in separating promising solutions from the bad ones. The pheromone also “evaporates”, meaning that
it can decrease over time. The goal is to make good solutions more attractive for the ants in the next iteration. The pseudocode of ACO is given in figure 1(b) [9][14].

```
1 Initialize the population with random individuals
2 Evaluate each individual
3 repeat
   4 Select parents
   5 Recombine pairs of parents
   6 Mutate the resulting offspring
   7 Evaluate new individuals
   8 Select individuals for the next generation
3 until a termination condition is satisfied
```

(a)

```
1 Initialize pheromone values
2 while termination condition not met do
   3 Construct Ants Solutions
   4 Update Pheromones
   5 Daemon Actions
3 end
```

(b)

Figure 1. Pseudocodes of selected metaheuristics. (a) GA; (b) ACO.

3.1. Comparisons of GA and ACO

There are many comparisons that have been done between the two metaheuristics for many problems in various fields. Gill et al. [15] have applied both methods for very-large-scale integration (VLSI) circuit partitioning where GA produces consistently better average result than ACO over all instances [15]. Patha et al. [16] test them for solving traffic signal coordination and they conclude that ACO is better for solving very complicated networks [16]. ACO is also observed to perform better than GA in solving energy efficient coverage in wireless sensor networks [17]. Jiang et al. [18] use the metaheuristics to optimize automatic seeding transplanters. The performance of ACO is found to be more efficient than GA, but it is more time-consuming [18]. Katona et al. [19] work on the parallel implementations of both GA and ACO for multimodal transport systems optimization. They have determined that ACO is suitable when the network structure is unknown, while GA is robust against failures and network errors [19]. In the case of TSP, there are two recent studies. Alhanjouri and Alfarra [20] deduce that GA is better than ACO. However, K. Arora and M. Arora [11] results suggest otherwise. GA is found to be better in lower numbers of cities which agreed the previous study, but it is bested by ACO at higher complexity. In terms of execution times, ACO is always better [11].

3.2. Suitability of ACO for shielding optimization

The ACO was developed to solve COPs which have practical implementation in the real world. One of the original COPs was the TSP mentioned in Section 2. In recent studies, it has been applied in many engineering problems. They include job scheduling, structure, digital image processing, power engineering, clustering, and routing [21]. Maier et al. [22] showed that ACO was an attractive alternative to genetic algorithm (GA) for water distribution systems [22]. Their work was expanded to include pumping station, storage, multiple extended period loading conditions [23]. In structural design, ACO had been applied to optimize the weight of transmission tower [24], space trusses [25], steel frames [26][27], truss topology [28], and cost of tall bridge piers [29]. Aydoğdu & Saka [30] extended the optimization of steel frames by including the effect of warping in irregular frames which was shown to possibly yield an unsafe design if it is not taken into consideration. Multilayer shield problem, like other engineering problems, can also be considered as a COP as the designer need to choose between combinations of materials that can fulfill the requirements of the shield.

Most of the above examples were modified from the original TSP optimization. While the TSP concerns the total distance travelled by the salesman, the structural optimizations were focused on achieving the least weight possible which is directly related to the cost of the structure. For example,
as shown in the work of [26], they use ACO to determine the best combinations of W-shape members that result in minimum weight while satisfying standard specifications. This can be applied to multilayer shield optimization where the ACO can be used to identify the most optimum combination of materials, arrangements, and layer thickness that result in the best shielding performance.

4. Proposed Work with ACO

Based on the previous examples, it can be said that GA and ACO have their own advantages for different applications. However, in terms of radiation shield optimization, it is yet to be determined how ACO would perform. The only work that had been done using GA was the study by Hu et al. in [31]. They designed a multilayer composite shield for mixed neutron and gamma rays using GA combined with the Monte Carlo N-Particle (MCNP) code which is an internationally recognized code for analyzing the transport of neutrons and gamma rays. It also deals with coupled transport which is the transport of secondary gamma rays resulting from neutron interactions. The flow chart of the algorithm and MCNP simulation are shown in figure 2(a) and 1(b) respectively. The algorithm was written to produce combinations of materials contents of composites that can minimize the amount of radiation dose. However, the authors did not include the details of the GA itself. Pseudocode of a typical GA is provided in figure 1(a).

The algorithm managed to generate five composite materials. Each of them had different percentages of elements and densities. These new materials showed good shielding performance when compared to lead oxide. They had also designed multilayer shields named “cakes” where GA was used to determine the optimum thickness ratios of individual layers. Four of the composites were manufactured and experimentally evaluated. The MCNP simulation data showed good agreement with experimental data for thickness less than 10 cm before dose buildup effect occurred. The authors concluded that the GA and MCNP code can be applied to optimize lightweight, compact, and heat resistant material for mixed radiation shields.
Based on the previous work, we would like to outline the approach of developing ACO for multilayer shield design. The flow chart of the algorithm is shown in figure 3, while the MCNP model is shown in figure 4. The objective function is shown below.

\[
\text{minimize } H(A,X) = H_n(A,X) + H_g(A,X)
\]

where,

- \(H(A,X)\): Total equivalent dose from neutrons and gamma-rays penetrating the shield of arrangement \(A\) and layer thickness \(X\), Sv
- \(H_n(A,X)\): Equivalent dose from neutrons, Sv
- \(H_g(A,X)\): Equivalent dose from gamma-rays, Sv
- \(A\): Arrangement of materials
- \(X\): Set of thicknesses of individual layers in \(A\)

**Figure 3.** ACO algorithm flow chart for a multilayer shield

**Figure 4.** Illustration of MCNP simulation
Based on the pseudocode in figure 1(b), the algorithm will start by initializing the pheromone value for each of the possible solutions which are usually set to a value greater than zero [32]. In the first iteration, all of the possible solutions will have equal probability to be chosen by the artificial ants. A large number of ants is recommended to reduce the random fluctuations and to reduce the number of iterations for convergence [13]. Then, each of the ants will randomly choose one of the shield design solutions. In this case, a candidate solution is generated when an ant has picked the candidate materials, their arrangement, and the thickness of each layer. This three information will be exported to MCNP to calculate the equivalent dose on the outer layer of the shield as shown in figure 4.

The pheromone update will be carried out based on the dose of each of the solutions chosen by the ants. The lower the dose of a solution, the higher the pheromone will be added to the solution, following the rule of equation 2. Furthermore, the pheromone value for each solution will also undergo evaporation at the end of each iteration at the rate based on Equation 3. This step is crucial and must be carefully set, otherwise the algorithm may not converge to the most optimum solution [11][14].

\[
\tau(A_i, X_i) \leftarrow \tau(A_i, X_i) + \frac{Q}{H(A_i, X_i)} \quad (2)
\]

\[
\tau(A_i, X_i) \leftarrow \tau(A_i, X_i) (1 - \rho) \quad (3)
\]

where

- \( \tau(A_i, X_i) \) : Pheromone value associated with solution of arrangement \( A_i \) and thickness \( X_i \)
- \( Q \) : Constant value
- \( H(A_i, X_i) \) : Total equivalent dose, Sv
- \( \rho \) : Evaporation rate of pheromone values

After the pheromone update, the algorithm will check for termination condition. In this case, the algorithm may be terminated after a certain number of iterations. If the condition is not met, a new iteration will begin with the previous update pheromone values. This is one of the main characteristics of ACO where a history of the previous generation is preserved for future improvements of solutions as opposed to GA where the history of the parent generation will be eliminated when the daughter generation is created. After the algorithm terminates, the solution that has the highest amount of pheromone value should be the best design for the radiation shield for the given set of materials.

5. Conclusion

The review of metaheuristics GA and ACO were provided. The application of metaheuristics for shielding optimization is found to be lacking as only GA had been implemented for such COP. ACO is chosen because it has been compared to GA in many optimization problems. A proposal for the development of an optimization algorithm based on ACO for multilayer shield against mixed neutron and gamma radiations is also given. The versatility and problem-independence of metaheuristics mean that they can be modified to optimize shields for other applications. The algorithm should be helpful to researchers in creating new shield materials, and engineers in designing a shield with any material available to them.
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