

# Optimal Path Planning in a Real-World Radioactive Environment: A Comparative Study of A-star and Dijkstra Algorithms

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## Abstract

Navigating complex radioactive environments while minimizing radiation exposure to workers is a critical challenge faced by the nuclear industry. Although various shortest-path algorithms and radiation dose calculation techniques have been employed for optimal path finding, most existing models are based on simulations that do not accurately represent real-world environments. To address this limitation, this study presents a path-planning experiment conducted on a naturally radioactive slag dump, Slag Dump No. 48, also known as Black Mountain, in Zambia. The experiment utilizes the Radiation Detection Backpack System (RDBS) and Geolocation Application for Radiation Monitoring (GARM) in conjunction with the Dijkstra and A-star algorithms to search for an optimal walking path on the slag dump. The distances between neighboring nodes and heuristic values, derived from gamma dose rates, are experimentally obtained from the GARM software. This research contributes to the field by: (1) performing a real-world path planning experiment on a radioactive slag dump, (2) applying RDBS for measuring gamma radiation from a naturally radioactive slag, (3) investigating the combined use of RDBS, GARM, Dijkstra, and A-star algorithms for optimal path finding, (4) generating heuristic values and node distances experimentally for path planning in an actual radioactive environment, and (5) comparing the performance of state-of-the-art minimum dose walking path algorithms on dose rate-based and node distance-based weighted graphs. The results of this study and the proposed future work provide valuable insights for enhancing radiation protection and optimizing path planning in radioactive environments.

**Keywords:** Optimal path planning; Radiation Dose Assessment; Gamma radiation; A-star Algorithm; Dijkstra algorithm; Nuclear decommissioning

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## 1. Introduction

Nuclear energy has been widely utilized for various power and non-power applications, providing substantial benefits to human society. However, ensuring safety is of paramount importance when dealing with radioactive facilities, as the potential for radiation exposure poses significant risks. In recent years, researchers have focused on developing optimal walking path algorithms to minimize the accumulated radiation dose for workers navigating through complex radioactive environments.

A range of shortest-path algorithms and applications have been studied for minimum dose path planning [1]–[9]. Different techniques of calculating radiation dose [10] [11] have also been employed in these path-planning problems. Radiation dose calculation techniques, such as Monte Carlo methods (e.g., MCNP, Geant4, FLUKA) and analytical point-kernel methods (e.g., Microshield, QAD, Mercure) [12]–[14], have been employed in these path-planning problems. While point-kernel methods are simple, they are often inefficient for complex environments. In contrast, Monte Carlo methods perform better in handling intricate calculations. By integrating these techniques with shortest-path algorithms, such as Dijkstra, A\*, rapidly exploring random tree (RRT) RRT, and Particle swarm optimization (PSO), radiation protection in radioactive environments can be significantly enhanced [2].

Similarly, there are several types of facilities and environments that do not solely use radioactive sources for various applications. Slag dumping sites are examples of environments that do not necessarily use radiation but contain enhanced naturally occurring radioactive materials (NORM) and contribute to natural radiation. Consequently, human activities being conducted on radioactive slag dump will result into radiation exposure of people and when the natural radiation is enhanced over exposure is a risk to human health. Therefore, minimum dose path planning is key to ensuring optimization of radiation protection and the personnel navigating the radioactive slag dump will receive the least amount of radiation.

However, existing optimal dose path search approaches predominantly rely on simulations within radioactive environments, and radiation dose computation is based on analytical and Monte Carlo methods. Although path planning and environmental simulation of nuclear facilities are convenient and time-saving, these models often fail to accurately represent the actual radioactive environments, leading to sub-optimal pathfinding. To address this issue, the present study conducts a path-planning experiment on a radioactive slag dump (Nkana Slag dump) in Zambia, commonly known as Black Mountain. The gamma radiation detected at the site originates from the elevated concentration of NORM in the slag.

This research investigates the application of the Radiation Detection Backpack System (RDBS), Geolocation Application for Radiation Monitoring (GARM), Dijkstra, and A-star algorithms to search for an optimal walking path on the Nkana slag heap. The GARM software is employed to obtain the distances between neighboring nodes ( $g(n)$ ) and heuristic values ( $h(n)$ ) for the navigation points, with the latter being the evaluated gamma dose rates. This work makes the following contributions to the field:

- i. Conducting a real-world path planning experiment on a naturally occurring radioactive slag dump.
- ii. Applying the RDBS to measure gamma radiation emitted from a slag dump consisting of NORM.
- iii. Investigating the application of the Radiation Detection Backpack System (RDBS), Geolocation Application for Radiation Monitoring (GARM), Dijkstra, and A\* algorithms to search for an optimal walking path on a slag heap.
- iv. Experimentally generating heuristic values ( $h(n)$ ) and node distances ( $g(n)$ ) for path planning in a real radioactive environment.
- v. Comparing the performance of state-of-the-art minimum dose walking path algorithms on a dose rate-based and node distance-based weighted graph.

By addressing these research objectives, this study aims to provide valuable insights into enhancing radiation protection and optimizing path planning in radioactive environments.

## **2. Method and materials**

### **2.1. Slag dump**

The Nkana Slag Dump No. 48 (The Black Mountain) located in Kitwe district of Zambia, has existed since 1931 when the Nkana copper smelter was commissioned. These 20 million tonnes of smelter slag contain about 0.34 per cent - 4.5 per cent cobalt and average 1.2 per cent copper[15]. The slag dump is a radioactive environment emitting gamma, alpha and neutron rays from the natural Uranium decay series contained in the slag dump. Figure 1 shows a satellite view of the dump. In this work, the minimum dose path is evaluated on the slag dump. To obtain radiation dose rates for A-star algorithm implementation, radiation detection backpack system (RDBS) was used to detect and measure the radiation dose. The backpack was lifted to an average high of 1 metre from the ground. The physical navigation of the slug dump area included walking with the RDBS. The system recorded both gamma and neutron radiation together with the GPS coordinates, ambient temperature and acquiring time at each location. The recorded information was then uploaded into the geolocation application for radiation monitoring (GARM) software. Analysis conducted on the uploaded values includes radiation distribution, visualization, spectrum and generation of A-star algorithm parameters, heuristics  $h(n)$  and distance between the selected node  $g(n)$ .

### **2.2. Radiation Detection Backpack System**

The Radiation Detection Backpack System (RDBS) is a radiation monitoring system used for the detection of radiation sources. It is an effective detection system that can monitor areas, buildings routes, etc with GPS referencing. Illicit activities such as storage, use, and transfer of radiation sources can be detected with RDBS and prevention of radiological threats. Figure 2 shows the RDBS (AT6101CM) spectrometer system used in the experiment to measure and detect radiation. The detection unit consists of NaI(Tl)-based spectrometric gamma radiation detection, and Helium-3-based neutron radiation detection and was rugged with an Windows operated NAUTIZ X8 handheld smartphone for control, storage and display of data. The purpose of the smartphone is for the operator to hear a corresponding voice message in a wireless headset and see the displayed types of radionuclides identified.



**Legend**  
[Red outline] Slag Dump No.48

**Slag Dump No.48**

0 0.125 0.25 0.5 Kilometers



Figure 1: Satellite map of the Nkana slug dump

By placing the RDBS at the back, and walking through the slag dump, the spectrometer operated in the continuous radiation environment scan mode. The scan results were continuously saved into the memory for further processing and analysis on a computer using the 2656 Geolocation application for radiation monitoring (GARM) software described in Section 2.3. With the GARM software, the results were mapped for visualization and minimum dose path planning.



Figure 2: The RBDS bag contains a Gamma detector, a Neutron detector, Bluetooth Transmitter and Handheld receiver.

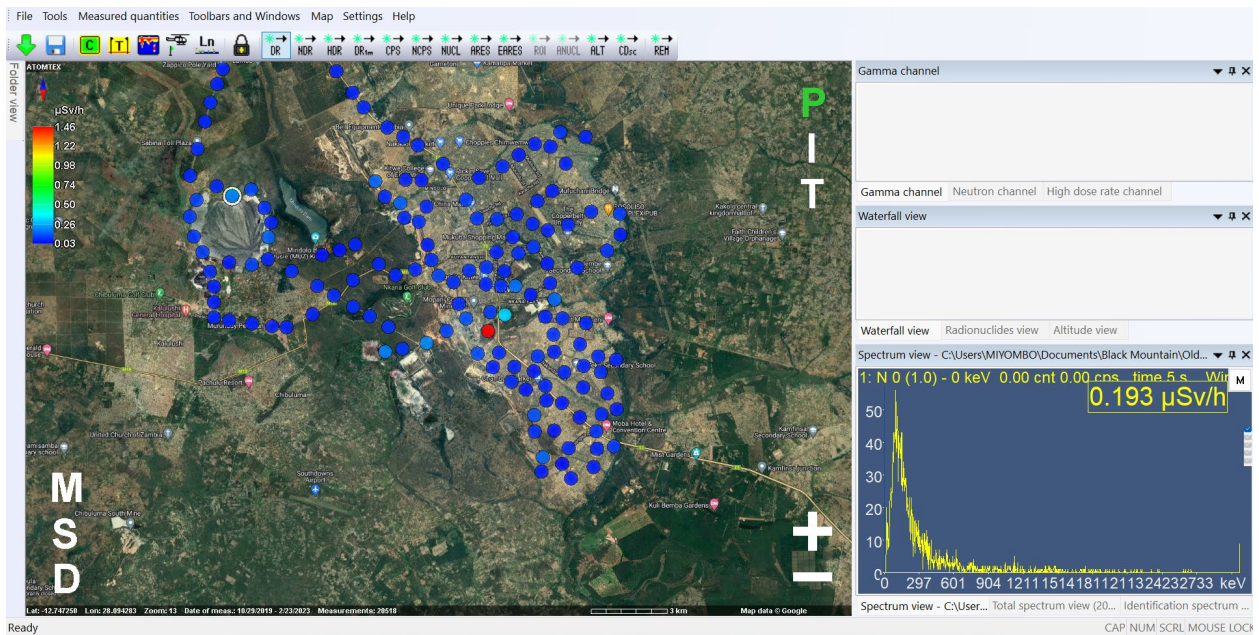


Figure 3: The GARM window and interface. The blue dots show radiation dose rates obtained by the RBDS during navigation.

### 2.3. Geolocation Application for Radiation Monitoring (GARM)

The "GARM" (Geolocation Application for Radiation Monitoring) is a software developed by ATOMTEX. It is designed to analyze and visualize radiation scanning data with GPS-referencing like spectra, gamma radiation dose rate, gamma and neutron radiation impulse count rates, and radionuclide composition identification results in the form of graphs and map waypoints. The A-star algorithm uses heuristics to search for the shortest path in a navigation area. To achieve this objective, GARM was used in this study to obtain the nodes (location of navigation points), dose rates and the distance between the nodes. Evaluation of distances between nodes in the conventional approach is generally computed by assuming the navigation area is a flat surface. This assumption is inappropriate when dealing with a real environment. For efficient results and accurate computation, GARM software was also used to evaluate distances between nodes.

### 2.4. Path planning Algorithms

#### 2.4.1. Dijkstra algorithm

Edger Dijkstra, a Dutch computer scientist created one of the earliest shortest-path algorithms in 1959 [16]. The algorithm finds the shortest path  $G$  from a starting node to a destination node in a directed graph  $G(V, E)$  if all nodes have non-negative weights where  $G(V, E)$  denotes the set of nodes ( $V$ ) and edges ( $E$ ). Firstly, from the initial node, the algorithm searches for the optimal path by setting all other node distances to infinity, and then all adjacent nodes are relaxed from the occupied node. The next node to be occupied is the adjacent node with the least cost. The relaxation process is repeated until the final node is reached. Let  $c(u, v)$  be the cost from  $u$  to  $v$  where  $u$  is the occupied node and  $v$  is the adjacent node, then if  $d(u) + c(u, v) < d(v)$ ;  $d(v) = d(u) + c(u, v)$ . Here  $d(u)$ ,  $d(v)$  are the weights of nodes  $u$  and  $v$  respectively. Table 1 shows the Dijkstra's algorithm description.

Table 1: Dijkstra's algorithm

1.	<b>function</b> <i>Dijkstra</i> ( <i>Graph</i> , <i>source</i> ):	
2.	<b>for each</b> vertex $v$ in <i>Graph</i> :	# initialization
3.	$dist[u] \leftarrow infinity$	# set initial distance from source to vertex $v$ to infinity
4.	$previous[v] \leftarrow undefined$	# previous node in the optimal path from source
5.	$dist[source] \leftarrow 0$	# source to source cost
6.	$G \leftarrow set\ of\ all\ nodes\ in\ the\ Graph:$	# unrelaxed nodes in $G$
7.	<b>while</b> $G$ is not empty:	# The main loop
8.	$u \leftarrow node\ in\ G\ with\ smallest\ dist[ ]$	
9.	remove $u$ from $G$	
10.	<b>for each</b> neighbor $v$ of $u$ :	# where $v$ has not yet been removed from $G$ .
11.	$alt \leftarrow dist[u] + c(u, v)$	# $c(u, v)$ distance from $u$ to $v$
12.	<b>if</b> $alt < dist[v]$	# relax ( $u, v$ )
13.	$dist[v] \leftarrow alt$	
14.	$previous[v] \leftarrow u$	
15.	<b>return</b> $previous[ ]$	

#### 2.4.2. A-star algorithm

A\* algorithm is a grid-based shortest-path search algorithm developed by Hart et al. [17]. It has been used in several shortest-path problems to search for the minimum cost path from the starting point to the end point[18], [19]. Due to its high performance and less computational overhead, it is an effective path search algorithm in different disciplines, including satellite navigation for road vehicles and path planning for robots and vehicles[20]–[22]. The A-star algorithm operates under the principle of computing the cost  $f(n)$  to travel to all the adjacent nodes ( $n$  is the adjacent node). The objective of A-star is it enter a state (node) with the lowest value of  $f(n)$  given by the following expression:

$$f(n) = g(n) + h(n) \quad (1)$$

where  $g(n)$  is the known distance (or cost) from the start node to the current node  $n$ , and  $h(n)$  is the heuristic estimation of the nodes' value. Thus, in every search step, the node with the lowest value of  $f(n)$  is chosen as the next one to expand. To implement the A-star algorithm in this experimental work,  $g(n)$  values or the distances between adjacent nodes on the slag damp were evaluated using the advanced GARM software. Meanwhile, this experiment applied the gamma dose rate as the heuristic value,  $h(n)$ . The dose rate was also obtained from the GARM software installed on the computer and capable of analyzing data that was uploaded from the RDBS system. Table 2 describes the basic pseudocode for the implementation of the A-star algorithm.

Table 2 A\* Algorithm

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OPEN list= [array of generated nodes but not visited]  
CLOSE = [ array of visited nodes]

- 1: OPEN list  $\leftarrow$   $P[start\ node]$
- 2: Find  $f(n)$  of  $P[start\ node]$
- 3: Remove the node  $P[i]$  with smallest  $f(n)$  from OPEN list
- 4: If  $P[i]=P[Goal\ node]$   
    **STOP**  
    RETURN to success
- 5: **Else**
- 6: Remove  $P[i]$  from OPEN list and find its successors
- 7: Find  $f(n)$  of all  $P[successors]$
- 8: OPEN list  $\leftarrow$   $P[successors]$  and
- 9: CLOSE list  $\leftarrow$  removed  $P[i]$
- 10: Go to STEP 3
- 11: **EXIT**

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### 3. Experiment and results

The minimum dose path planning experiment was conducted by: selecting the slag dump; detecting radiation using RDBS, analysing and visualising radiation scanning data with GPS referencing with GARM software; setting navigation nodes, implementing the A-star shortest path algorithm and obtaining the optimal path yield the least amount of radiation. The minimum dose path planning experiment is summarized in the flow chart in *Figure 4*.

#### 3.1. Navigation space selection (slag Dump No. 48)

The slag dump described in Section 2.1 is the actual radioactive environment. The slag dump is a copper smelter waste product with a top walking surface shown in *Figure 5*. The path planning experiment was conducted on a region covering a perimeter of 1, 829.6 m of the slag dump. It is the main region of the slag dump on which small-scale miners walk in search of precious minerals.

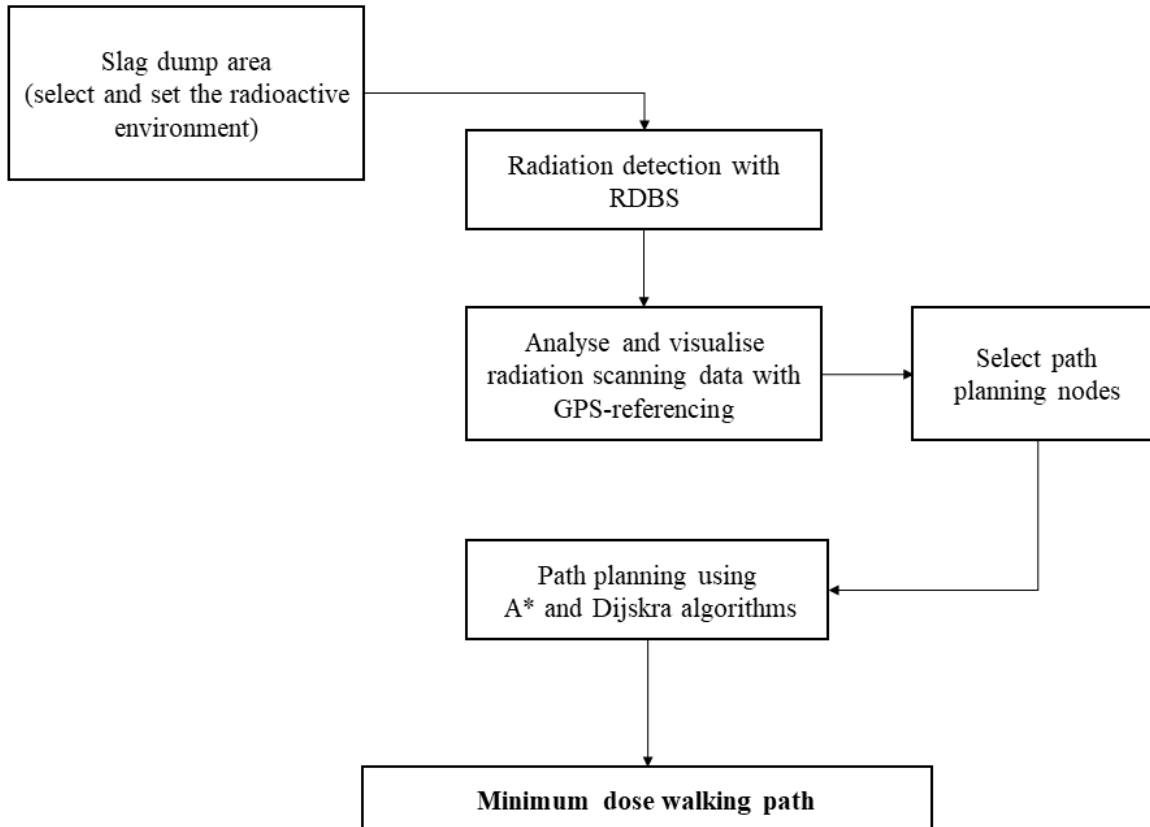


Figure 4 Experiment path planning flow chart



Figure 5: The slag dump walking surface as seen from the top surface.

The slag consists of tiny, small and large particles (ores) but the surface is walkable and accessible. Most importantly, the slag is the source of the natural gamma radiation that was detected, measured and analysed for path planning objectives. Through observation, the region of interest was identified physically while the distance between navigation nodes was evaluated from GARM software.

### **3.2. Radiation detection, dose analysis and visualization**

Detection of radiation is a key element in solving the shortest path problem in radioactive environments. The radiation dose is required for radiation protection optimisation. For optimal path search, the dose is needed for the computation of heuristic values especially when the A-star algorithm is being used for path planning. The traditional path-planning approaches rely on point-kernel (analytical) and Monte Carlo-based radiation computation. This is done using environmental models and simulations and as a consequence path planning results may not exact or represent the real environments. Thus, this study investigated the application of actual radiation detectors in a real radioactive environment to develop an algorithm for minimum dose path search. Radiation detection in the region of interest of the slag dump was done through walking surveys. Placing both the gamma detector and neutron detector in the bag as shown in Figure 2, the RDBS is portable and easy to use during walking surveys in the region of interest of the slag dump.

The RDBS has four, gamma detector, neutron detector, Bluetooth transmitter and handheld data collector connects seamless to each other as part of the radiation detection system. The data collector was responsible for storing information while the smartphone was responsible for displaying the radiation spectrum and types of identified radionuclides. By carrying the RDBS on the back, and use of the handheld smartphone in the hands, the selected area on the slag dump was scanned and radiation detection was achieved. Meanwhile, the RDBS continuously saved the scan results into memory. After the walking survey on the slag dump was completed, the saved scan results were processed and analysed using the GARM software. Analysis of results involved mapping and radiation dose rate distribution in  $\mu\text{Sv/h}$  of the region of interest was made.

Figure 7 shows the radiation hot spots on the slag dump and the existing walking paths. The RDBS data contained radiation dose levels below the background radiation and above. Therefore, to select and design an optimal path problem, this study considered only nodes whose radiation dose rate values (heuristic) were above the natural background radiation in the region.

### 3.3. Description of the shortest path problem

The slag dump shown in Figure 1 and

Figure 7 has a controlled access area. The area of interest has 22 nodes covering a perimeter of 1,829.6 m. Thus, the shortest path problem to be solved in this work using the Dijkstra algorithm and A-star algorithm is to determine the shortest path that yields the least possible amount of radiation dose from any START node to a GOAL node. In

Figure 7 radiation hot spots of varying dose levels can be seen within the region of interest. Thus, the objective of the path planning is to optimize radiation protection by ensuring that an optimal walking path is used from START to GOAL. The spectrum of the maximum radiation dose is given in Figure 6. The slag dump consists of existing walking paths, also connecting the 22 nodes described in Figure 7(b).

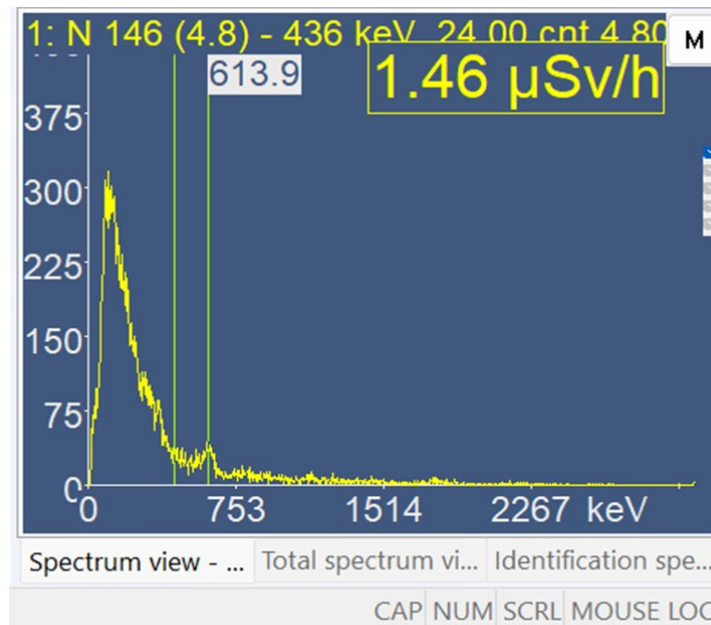
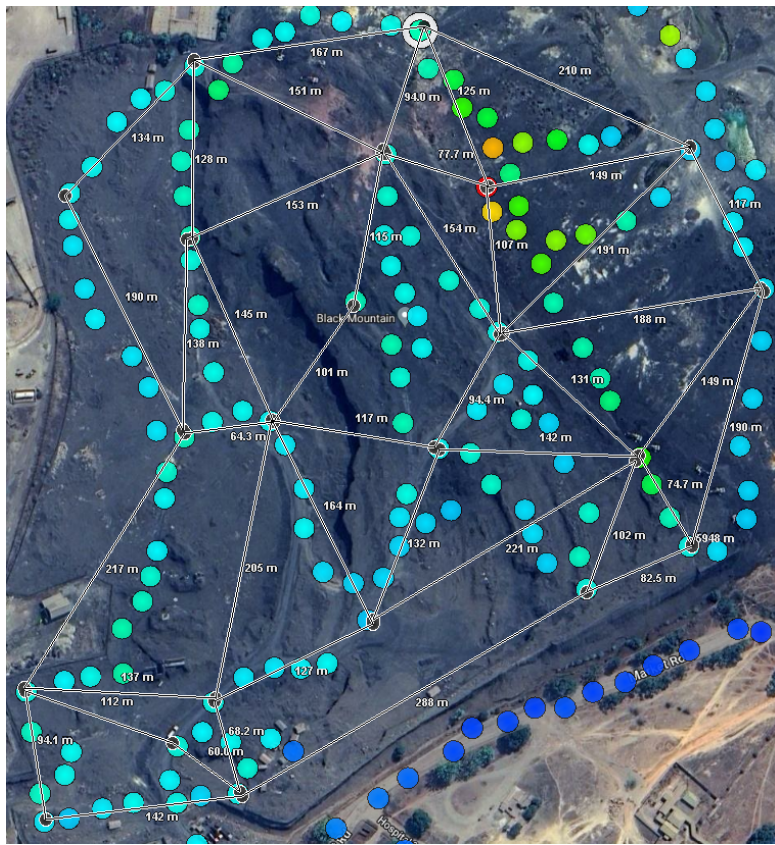
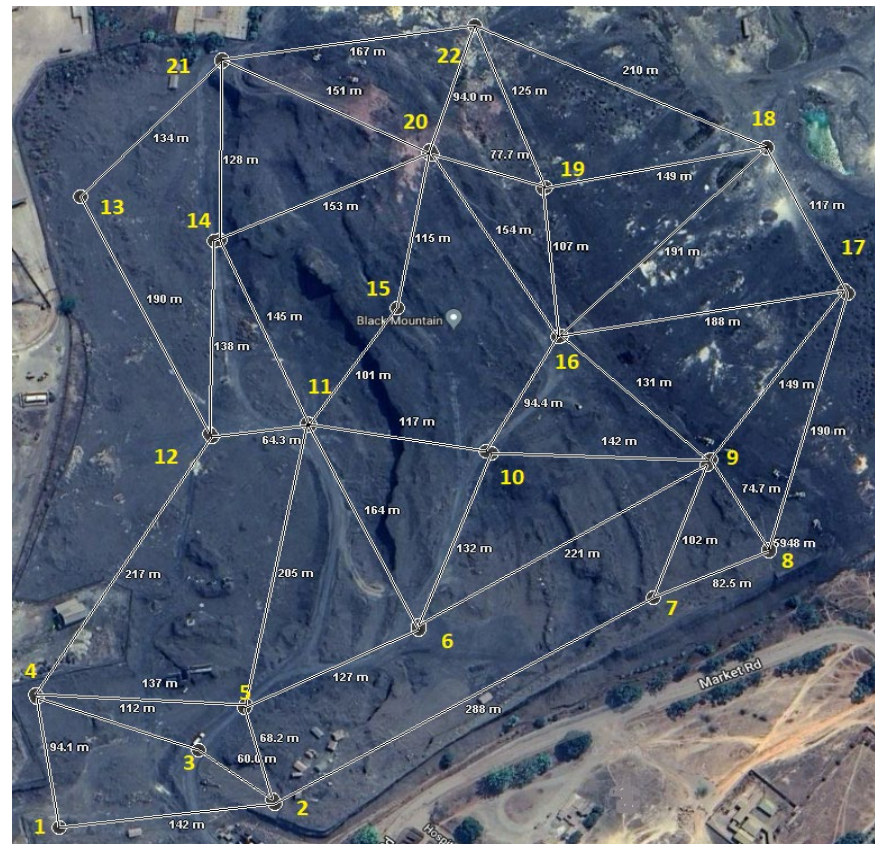


Figure 6: Radiation spectrum of the maximum node obtained from GARM software



(a)



(b)

Figure 7: The radiation dose distribution for (a) radiation hot spots on the slag dump- which also represent the navigation nodes from the radiation mapping of the area of interest on the Slag Dump; (b) The 22 nodes and edges representing the existing walking paths with known distances.

### 3.4. Path planning

#### 3.4.1. A-star algorithm

To solve the shortest path problem in the navigation area using the A-star algorithm, the algorithm requires two important inputs for the optimal path search state in Eqn.(1). That is, the function  $f(n)$  enters the state of every node with the value of  $g(n)$  and  $h(n)$ . In principle, to implement the A-star algorithm, the navigation nodes must be known. Thus, 22 nodes that had heuristic values corresponding to dose rates above the background threshold were determined from the scan results as shown in Figure 7. GARM software was used to find  $g(n)$ , the known distance (or cost) from the start node to the current node  $n$  required for the implementation of the A-star algorithm. GARM software is an effective tool for the analysis and visualization of radiation with GPS referencing. In addition, all the distances between each adjacent node were computed and labelled as shown in Figure 7. The distances also known as edges denote the actual existing walking paths on the slag site. Moreover, there were no obstacles on these paths (edges) between every node.

The other important value needed to run the A-star algorithm is the  $h(n)$ , the heuristic estimation of the nodes' value. Two methods are commonly used to obtain the heuristic values  $h(n)$ . The exact value can be calculated but it is time-consuming. To minimize computation, the value of  $h(n)$  can be approximated from some heuristics. In addition, the overall choice will also depend on the type and nature of the shortest path problem being solved. For this study, the radiation dose rates (Table 3) obtained from the RDBS and the GARM software were the heuristic values for the A-star algorithm. Thus, to implement the A-star algorithm, the following assumptions were made: a) The walking speed is constant; b) Radiation dose rates were the heuristics.

In this study, the cost between two adjacent nodes  $g(n)$  and the approximated heuristic  $h(n)$  have different results. Hence the sum of these two values yields trivial results with establishing justifiable computations. Thus, the study has adopted the sum of the known distances and the dose rates to obtain the function  $f(n)$  of the algorithm. The mathematical computation is reasonable because, of the basic law of mathematics, the Distributive Law. Even if some constants were introduced to convert the two terms  $g(n)$  and  $h(n)$  into the same quantities, the proportional distribution on all the nodes and edges will not affect the results and optimal path. The A-star algorithm described in Section 2.4 and Table 2 was implemented with Python computer codes. In the programme, a function was defined to return heuristic dose rates for all the nodes. Then, the graph of nodes was defined. This graph of nodes describes how the 22 nodes are connected with the known distances using the following pseudo code:

$P_1: [(Adj_i, r_i), (Adj_{ii}, r_{ii}), \dots (Adj_n, r_n)],$   
 $P_2: [(Adj_i, r_i), (Adj_{ii}, r_{ii}), \dots (Adj_n, r_n)],$   
 $P_3: [(Adj_i, r_i), (Adj_{ii}, r_{ii}), (Adj_{iii}, r_{iii}), \dots (Adj_n, r_n)],$   
:  
:  
 $P_N: [(Adj_i, r_i), (Adj_{ii}, r_{ii}), \dots (Adj_n, r_n)],$

where  $P$  is the node,  $N$  is the number of nodes, and  $Adj_n$  is the number of adjacent nodes of every node. This graph together with the distance function was part of the A-star algorithm used to obtain the minimum dose paths for two scenarios shown in *Figure 8* and total physical distances in *Table 5*.

### 3.4.2. Dijkstra Algorithm

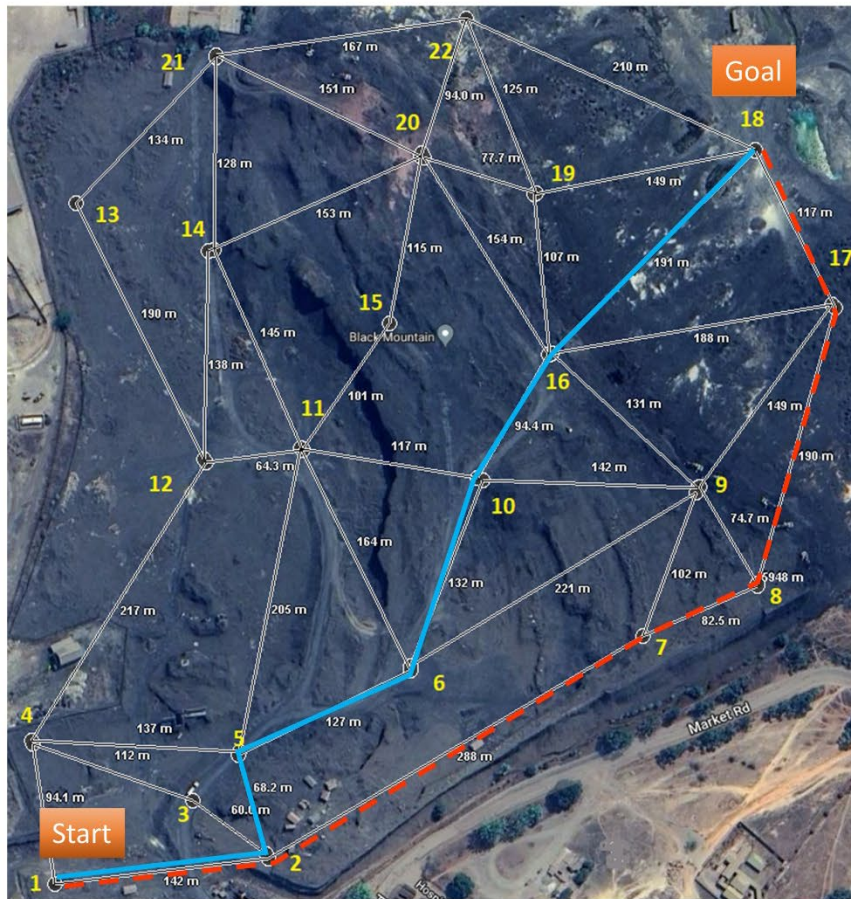
Let  $c(u,v)$  be the cost from  $u$  to  $v$  where  $u$  is the occupied node and  $v$  is the adjacent node. Hence:

$$\begin{aligned} \text{If } d(u) + c(u, v) < d(v); \text{ then} \\ d(v) = d(u) + c(u, v) \end{aligned} \quad (2)$$

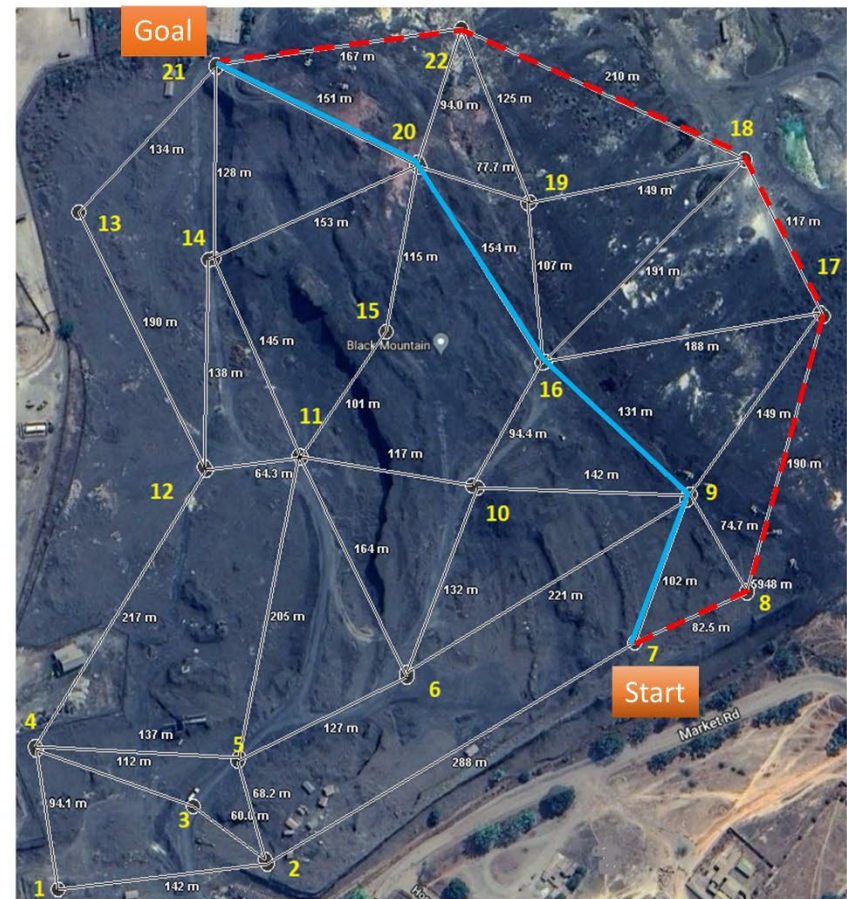
where  $d(u)$ ,  $d(v)$  are weights of nodes  $u$  and  $v$  respectively. Because the Dijkstra algorithm does not use heuristics, this work investigated its performance in two approaches of computing weights: (a) the cost of travel between adjacent nodes (distance between nodes) and (b) the radiation dose values. *Figure 8* shows the optimal path obtained from the Dijkstra algorithm using two different types of weighted graphs. The total physical distances from START to Goal are given in *Table 5*. The table compares the total distances of path RED, and BLUE covered when walking from START to GOAL for both SCENARIOS I & II

Table 3 Radiation dose rates

Node #	Dose rate $\mu\text{sv/h}$
1	0.35
2	0.4
3	0.38
4	0.42
5	0.43
6	0.35
7	0.42
8	0.35
9	0.78
10	0.4
11	0.4
12	0.45
13	0.4
14	0.49
15	0.48
16	0.43
17	0.36
18	0.32
19	1.46
20	0.44
21	0.42
22	0.49



(a)



(b)

Figure 8: Optimal walking paths: (a) SCENARIO I- BLUE path is optimal path obtained from A\* and Dijkstra algorithm (using distance between nodes as weights). The RED path is found with Dijkstra algorithm searching with radiation doses as weights; (b) SCENARIO II- The BLUE path is the minimum dose walking path found with the A\* search and Dijkstra algorithm (in which distance between nodes as weights). The RED path is found with Dijkstra algorithm searching with radiation doses as weights.

Table 4 Minimum dose results and computation time

Direction		Cumulative radiation dose ( $\mu\text{Sv}$ )			Computation time (ms)		
START	GOAL	Dijkstra**	Dijkstra***	A-star	Dijkstra**	Dijkstra***	A-star
1	18	2.2	2.68	2.68	1	1	2
7	21	2.36	2.49	2.49	1	1	3

\*\* Dijkstra algorithm using dose rates

\*\*\* Dijkstra algorithm using distance weights

Table 5 Physical distance from the START node to the GOAL node

Path	Scenario 1		Scenario 2	
	Total physical distance from START to GOAL (m)	Dose at the Goal ( $\mu\text{Sv}$ )	Total physical distance from START to GOAL (m)	Dose at the Goal ( $\mu\text{Sv}$ )
BLUE	754.6	2.68	538	2.49
RED	827.5	2.2	766.3	2.36

#### 4. Discussion

For the gamma radiation detected from the dump site, the annual dose limit for members of the public is 1 mSv which corresponds to the natural radiation exposure of a maximum of 0.3  $\mu\text{Sv/h}$ . Thus, dose rates above this value will potentially exceed the annual dose limit for the members of the public and persons exposed to such radiation should be considered occupationally exposed workers and must be monitored according to the national radiation safety requirements. The walking surveys generated several radiation hot spots along the existing walking path on the slag dump as shown in Figure 7. The hot spots have different dose rate values. To investigate a minimum dose walking path for occupationally exposed workers, this study concentrated on the radiation hot spots with radiation dose rate values  $\geq 0.35 \mu\text{Sv/h}$ . Consequently, for every existing walking path in Figure 7(a), only radiation hot spots with dose rates  $\geq 0.35 \mu\text{Sv/h}$  were considered and generated in the 22 nodes ( Table 3) and shown in Figure 7(b).

The A-star algorithm was implemented using distance heuristics to search for the optimal path, and the BLUE path was obtained in Scenario I. Meanwhile, the Dijkstra algorithm does not utilize heuristics, it is based on the cost of travel between two adjacent nodes. So, to compare the two algorithms, the study defined two approaches for the Dijkstra algorithm (i) radiation dose costs and (ii) node distances. These two types of costs were used to generate weighted graphs to implement the Dijkstra algorithm. The node distance weight-graph obtained the BLUE walking path obtained with the A-star algorithm, whereas the radiation dose weight-graph of the Dijkstra algorithm obtained the RED walking path.

The Dijkstra and A-star path planning algorithms obtained the optimal paths shown in Figure 8. Two scenarios on the slag dump were simulated by choosing two different sets of START and GOAL nodes. In the first scenario, nodes 1 and 18 were START and GOAL nodes respectively. The A-star algorithm uses heuristics. In this experiment, the RDBS, the GARM software and

mapping of the scanned results were used to generate the node distances and heuristics for A-star. The optimal path searched by the A-star algorithm in Scenario I is the BLUE solid path that travelled from START (node 1) to GOAL (node 18) as shown in Figure 8(a). On the other hand, the Dijkstra algorithm does not use heuristics. It searches for the shortest path using the cost of travel between neighbouring nodes. This experiment and analysis of scanned results generated two important parameters: radiation dose rates and mapped distances between navigation nodes. In path planning, these parameters are some of the factors that are commonly used for pathfinding using weighted graphs. Thus, to investigate its performance, this work studied radiation dose rates and node distance as weights for the nodes. The pathfinding experiment for Scenario I using the Dijkstra algorithm found two different results to travel from START (node 1) to GOAL (node 18): by using distance as weights, the BLUE path was obtained (same as A-star) and by using dose rates as weights, the optimal path obtained was the RED dashed line Figure 8(a).

In the Scenario II in Figure 8(b), the START was node 7 while GOAL was node 21. Similar to the first scenario, the A-star algorithm obtained the BLUE solid line as the optimal path using its basic search principles of cost of travel between adjacent nodes and radiation dose rates as heuristics. Similarly, the application of distance between neighbouring nodes and the radiation dose rates as weights in the Dijkstra algorithm yielded two different walking paths. The use of the distance between adjacent nodes in the path search found the same BLUE solid line determined by the A-star algorithm while the weights from radiation dose rates obtained the RED dashed line Figure 8(b).

From Table 4, the paths obtained with the Dijkstra algorithm which uses the radiation dose rates as weights obtained the walking path with the least possible accumulated radiation dose. In the first scenario, the total accumulated dose rate at the GOAL of the RED path is 2.2  $\mu\text{Sv/h}$ . This value is reduced by a fraction of 0.82 compared with the accumulated dose rates of the BLUE solid line. Similarly, the walking path with the least amount of accumulated dose of 2.36  $\mu\text{Sv/h}$  at the GOAL is the RED dashed path found by the Dijkstra algorithm using weights of dose rates. The total dose rate accumulated at the goal is lower by a fraction of 0.94 than the BLUE solid path.

The aim of Table 5, was to compare the dose rate-based weighted graph to the distance-based weighted graph. The physical distances of the RED path (in both SCENARIOS I & II) are longer than the BLUE path. However, the accumulated radiation dose received from START to the GOAL on the RED path is less than the BLUE path. Even though the RED line is the minimum dose walking path in Scenario I, on the contrary, the total physical distance between the START and GOAL of the RED is longer than the physical distance of the sub-optimal BLUE path. This means that, if one person walks through the RED path and the other one uses the BLUE path at the same speed (the assumption used in this experiment), the person using the BLUE path will arrive first because the physical distance is shorter. However, this path does not yield the least possible accumulate dose at the GOAL. As shown in Table 5, the optimal path resulting in the least amount of radiation dose at the destination is the RED path.

This phenomenon explains why the experiment used two algorithms, the A-star algorithm and the Dijkstra algorithm to search for the optimal path on the slag dump. The real meaning of this phenomenon can be explained by the use of radiation dose rates as weights in the implementation of Dijkstra's algorithm. Similarly, the actual physical distance along the optimal RED path from START to GOAL in the Scenario II is also longer than the sub-optimal BLUE path. But the

radiation dose at the GOAL of the RED path is less than the BLUE path because the searching approach uses the radiation dose rates which play a huge role in radiation protection.

This work presents an innovative application of path planning algorithms in real-world radioactive environment. However, there are a number of limitations. First, the path planning experiment presented in this work did not consider obstacles because the walking surface on the slag dump was feasible without any obstruction. While the slag dump had an existing walking path, obstacles may arise and so path search in complex geometries is inevitable. Thus, to obtain an optimal result in an obstacle-filled environment this study may need to be improved. Secondly, the RDBS and GARM generated and mapped several radiation dose hot spots. However, only 22 nodes were used as navigation nodes arising from the annual dose limits of the public. Thus, the other nodes that were not considered may potentially alter the obtained results. Nevertheless, the current study has shown an experimental method of searching for an optimal path in a radioactive environment and the results show that the method is efficient in protecting workers from radiation risks and applicable to other radioactive environments such as nuclear decommissioning sites.

## 5. Conclusion

This work presents an experimental path planning on a slag dump emitting natural radiation. The method is based on the application of the Radiation Detection Backpack System (RDBS) and Geolocation Application for Radiation Monitoring (GARM), with the A-star and Dijkstra shortest path algorithms to search for an optimal walking path on the region of interest of the slag dump. The experiment results show that the RDBS and GARM software are adaptable to the application of the A-star algorithm because they can generate the distance between two nodes  $h(n)$  and the heuristic values  $g(n)$  of the navigation points effectively. In addition, the distance between adjacent nodes and the radiation dose are also important parameters for the implementation of the Dijkstra algorithm. The experimental results and analysis show that for graph-based algorithms such as A-star and Dijkstra, it is more efficient to use radiation dose cost in the weighted graph than distances between neighboring nodes. The result presents an optimal method of protecting workers in an actual radioactive environment using radiation detectors and path planning algorithms.

To improve on the results presented in this work and advance the state-of-the-art, the following areas can be considered:

1. Evaluation of additional path-planning algorithms: Investigating the performance of other path-planning algorithms and comparing their efficiency to that of the A-star and Dijkstra algorithms to further refine the available options for optimal path finding in radioactive environments.
2. Enhancements to the RDBS and GARM: Exploring potential improvements to the existing RDBS and GARM systems for increased accuracy and precision in radiation dose rate estimation and node distance measurement.
3. Integration of real-time data: Developing methods for incorporating real-time radiation data into path-planning algorithms to account for potential fluctuations in radiation levels and adapt the optimal path accordingly.
4. Dynamic path planning: Examining the possibility of implementing dynamic path planning, which would allow the system to modify its suggested route in response to changing environmental conditions, such as the movement of radioactive materials or unexpected obstacles.

5. Application in other hazardous environments: Investigating the potential applicability of the proposed path-planning methods in other hazardous environments, such as chemical or biological hazard sites, to broaden the scope of this technology beyond the nuclear industry.
6. Machine learning and artificial intelligence: Leverage advancements in machine learning and artificial intelligence to develop more sophisticated and efficient path-planning algorithms, which could further improve the safety and effectiveness of navigating radioactive environments.

The work presented in this paper, and the suggested future research direction could aid decision-makers and policy experts in developing and implementing advanced techniques and regulatory support for path planning in radioactive or hazardous environments.

### Acknowledgement

This research was supported by the Fundamental Research Funds for the Central Universities (NO. 3072022TS1501), the project of Institute of Computer Application, China Academy of Engineering Physics (NO. HT-2022-115), the National Natural Science Foundation for Young Scientists of China (Grant No. 12205065), the project of China Institute for Radiation Protection (NO. CIRP-CNNCRPTKLJJ003), Heilongjiang Natural Science Foundation (joint guidance) (NO. LH2021F002), the Fundamental Research Funds for the Central Universities (NO. 3072022JC0404).

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