Nuclear Engineering and Technology 53 (2021) 3505–3516

Contents lists available at ScienceDirect

Nuclear Engineering and Technology

journal homepage: www.elsevier.com/locate/net

Review Article

Path planning in nuclear facility decommissioning: Research status, challenges, and opportunities

Justina Onyinyechukwu Adibeli [a, b], Yong-kuo Liu [a, *], Abiodun Ayodeji [c, d], Ngbede Junior Awodi [a, d]

[a] Fundamental Science on Nuclear Safety and Simulation Technology Laboratory, Harbin Engineering University, Harbin, 150001, China
[b] Manpower Training and Capacity Development Directorate, Nigeria Atomic Energy Commission, Abuja, Nigeria
[c] State Key Laboratory of Industrial Control Technology, Zhejiang University, Hangzhou, China
[d] Nuclear Power Plant Development Directorate, Nigeria Atomic Energy Commission, Abuja, Nigeria

A R T I C L E I N F O

Article history:
Received 6 July 2020
Received in revised form
23 January 2021
Accepted 30 May 2021
Available online 4 June 2021

Keywords:
Nuclear decommissioning
Path planning
Radiation protection
Algorithms
Robotics
Dose assessment

A B S T R A C T

During nuclear facility decommissioning, workers are continuously exposed to high-level radiation. Hence, adequate path planning is critical to protect workers from unnecessary radiation exposure. This work discusses recent development in radioactive path planning and the algorithms recommended for the task. Specifically, we review the conventional methods for nuclear decommissioning path planning, analyze the techniques utilized in developing algorithms, and enumerate the decision factors that should be considered to optimize path planning algorithms. As a major contribution, we present the quantitative performance comparison of different algorithms utilized in solving path planning problems in nuclear decommissioning and highlight their merits and drawbacks. Also, we discuss techniques and critical consideration necessary for efficient application of robots and robotic path planning algorithms in nuclear facility decommissioning. Moreover, we analyze the influence of obstacles and the environmental/radioactive source dynamics on algorithms' efficiency. Finally, we recommend future research focus and highlight critical improvements required for the existing approaches towards a safer and cost-effective nuclear-decommissioning project.

1. Introduction

Nuclear decommissioning is a high-risk, labor-intensive activity, as there is a potential for a wide range of radiological and industrial accidents during the various stages of the task [1]. Decommissioning involves different activities such as cutting and re-sizing of components and equipment, solid and liquid waste removal, large structure demolition as well as handling of contaminated items [2]. All these activities are capable of producing hazards. Hence, it is pertinent that careful planning is put in place so that radiation exposure can be kept as low as reasonably achievable. This is also to ensure that the workers, the environment, and the public are protected from the harmful effects of radiation all through the decommissioning process. Path planning is a process used to determine an optimal path that a worker could take during decommissioning to reduce the radiation exposure. This is achieved by finding the path of minimum dose the worker should follow based on the calculated cumulative dose received by moving from one point to another along a radioactive path.

Some algorithms have been developed for this purpose. However, to the best of the authors' knowledge, there is no recent systematic review and discussion on the application of path planning algorithms in nuclear decommissioning. Moreover, in the literature reviewed, we observed gaps in the development and application of the algorithms from other industries for path planning purposes. For instance, some robotic algorithms are being introduced to nuclear decommissioning path planning. However, there are critical considerations for the efficient application of these algorithms into decommissioning.

This paper systematically reviews and categorizes current path planning algorithms. This work exhaustively discusses recent development in radioactive path planning and the proposed algorithms recommended for the task. Specifically, we review the conventional methods that are already in use for nuclear decommissioning, analyze the metrics and special techniques utilized in

* Corresponding author.
E-mail address: lyk08@126.com (Y.-k. Liu).

https://doi.org/10.1016/j.net.2021.05.038

the development of path planning algorithms, and enumerate the decision factors that should be considered to optimize path planning algorithms. As a major contribution, we present the quantitative performance comparison of different algorithms utilized to solve path planning problems in nuclear decommissioning and highlight their merits and drawbacks. Also, we discuss techniques and critical steps necessary for efficient application of path planning algorithms used in other fields, such as robotics, into nuclear facility decommissioning. Finally, we discuss the algorithm evaluation metrics and recommend future research focus towards improved and safe nuclear facility decommissioning.

This paper is organized as follows: section 2 is a brief background on the concept of path planning. The section also presents the basic algorithms available in path planning and the current theoretical approach in decommissioning projects. Section 3 presents the metrics considered in developing these algorithms. Multipath planning that involves generating paths for more than one worker at the same time is also discussed. Section 3 also presents the performance comparisons of different algorithms and the influence of obstacles and configuration space on the algorithms' efficiency in different environments. Section 4 explains the various factors to be considered when adopting path planning algorithms in robotics for a decommissioning project. The section also highlights the similarities and differences between path planning algorithms applied in nuclear decommissioning and robotics. It also discusses the merits and challenges in adopting robots for performing the decommissioning tasks. Finally, Section 5 summarizes and concludes the review.

2. A brief background on nuclear decommissioning path planning

Path planning involves finding the obstacle-free and optimal path for workers to navigate radioactive structures, components, and equipment to minimize radiation exposure dose. For a worker to move from point A to point B in a nuclear facility under decommissioning, the path planning problem is a search for the optimal path to follow with the lowest possible radiation exposure. This is accomplished by calculating the cumulative dose the worker receives in moving from one point to another along a path using the dose rate distribution map generated for the environment. This calculation is used to create an optimal path with the lowest radiation dose for the worker. Conventionally, the cumulative dose is calculated using the expression [3]:

$$D = \int_A^B \frac{R(i,j)}{v} ds \tag{1}$$

Where D is the cumulative dose along a given path, $R(i, j)$ is the dose rate at point (i, j) and v represent the average walking speed. This expression is applicable for a continuous radiation field where the radiation dose rate at any point can be measured directly. For a discrete radiation field, the situation is different as the radiation field is shown in a grid, and the dose rate at any point within the grid is estimated by interpolating between nodes. Further discussion on the path planning problem in nuclear decommissioning can be found in Ref. [3].

Path planning has grown in importance as decommissioning activities have become more prevalent and complex [4]. This is because the decommissioning task is continuously reviewed, with the changing environment. Hence, there is a need for a dynamic path planning technique to fit the changing environment. An efficient path planning algorithm for workers in a nuclear decommissioning project can be achieved by:

- Optimized sampling techniques [5–7].
- Effective node adding technique [6].
- Improved heuristics [4,6].

2.1. Metrics and considerations in developing path planning algorithms

The path planning technique chosen for a particular problem depends on the environment (static/dynamic, 2D/3D), the dose assessment method, the sampling technique, the collision detection technique, and the algorithm(s) selected. In a static environment, the obstacles do not change their positions with time, while in a dynamic environment, the obstacles change their positions with time. Major attributes of an effective path-planning algorithm are computation time, memory requirement, cost, simplicity, robustness, consistency, admissibility, completeness, optimality, effective path length, and dose rate calculation (for a high radiation field). An algorithm that generates an optimal path in the shortest possible time could influence the worker's performance.

Moreover, path planning in nuclear decommissioning involves calculating the radiation field using a dose assessment technique, generating a map based on the radiation field, performing collision detection after sampling, and using the algorithms to generate a safe path. The dose assessment techniques in use fall under two main categories: Monte Carlo (MC) techniques and the Point Kernel techniques. These are standard gamma dose rates calculation and radiation shield effectiveness methods for defined and arbitrary complex geometries. The Monte Carlo technique is based on the probability theory used in solving complex problems.

The Monte Carlo-based codes are the Monte Carlo Neutron Particle (MCNP) Transport code [8], FLUKA [9], GEANT [10] etc. MCNP has been proven to have the most reliable data on the characteristics of external radiation from radiating sources with complex geometry [11]. On the other hand, the point kernel (PK) technique is based on analytical calculations. It requires less time and can also produce accurate results with little variation compared with the MCNP. The codes that make use of PK technique include Mercure [12], MicroShield [13], QAD [14], etc. [15–17]. However, there are uncertainties in determining the build-up factor, further reducing the efficiency of the PK technique since the exact method is rather complex. Rudychev et al. [11] proposed a better way of calculating the build-up factor to calculate the dose rate correctly. The work recommends optimization schemes that include preliminary calculations using the point-kernel method with consequent Monte-Carlo simulation [11,18]. That is, applying the merits of the two approaches to get the best results.

The probability and non-probability sampling differ by whether or not the sampling selection involves randomization [19]. The non-probability approach is also referred to as deterministic or the exact approach. It involves following a set of defined steps to sample nodes used in generating a path for workers. While the deterministic model demonstrates better consistency and completeness, it requires a large memory. The probability category is also referred to as the stochastic or approximate approach. It is widely used since it randomly samples nodes used in generating paths for workers, but it does not necessarily yield the best solution. This approach is easier to implement than the deterministic technique, hence its widespread use. However, considering the merits and demerits of these approaches, the best technique is to adopt the deterministic model with little randomness [20].

Collision detection is a major part of path planning algorithm that determines the algorithm's efficiency. However, it is computationally expensive. Some techniques exist for collision detection and some of the effective collision detection procedures for sampling-based algorithms have been described [21,22]. Fig. 1 shows a flowchart for a typical path planning task during the decommissioning of a nuclear facility.

2.1.1. Common algorithms utilized for path planning and their applications in nuclear decommissioning

Standard path planning algorithms developed for decommissioning includes sampling-based algorithms such as rapidly exploring random tree (RRT) [23], probabilistic roadmap and their variants (PRM) [24,25], graph-based algorithms such as Dijkstra's algorithm [26,27], A* algorithm [28] and its variants, bio-inspired and other artificial intelligence-based models such as neural networks (NN) [29], genetic algorithm (GA) [30], particle swarm optimization (PSO) [31]and ant colony optimization (ACO) [32] or their combination [33]. There is also the hybrid approach, which combines two or more methods to obtain a better result.

The sampling-based algorithm is sub-divided into the active and the passive group. The active group, e.g. RRT, can independently generate a safe (minimum dose) path without retaining the memory of the roadmap by simultaneously growing a tree until the goal position is found. This is accomplished without relying on pre-designed road networks. It is also called a single-shot technique because it does not construct a retainable roadmap. The PRM falls under the passive group since it cannot independently find the best path. It is developed in two phases called the learning and query phases. It only generates a retainable roadmap from the start to the goal, and after that, utilize search algorithms such as Dijkstra to develop a feasible path [34]. It is also called the multi-query technique since the built roadmap can be used multiple times [33].

Graph-based algorithms generate a graph and subsequently find an optimal path based on the generated graph. The A* technique [28], an extension of the Dijkstra's algorithm [27], also uses the Manhattan or Euclidean Distance as the heuristic functions. These heuristic functions are used for cost estimation defined as:

$$(n) = (n) + h(n) \tag{2}$$

where *f*(n) is the cost between the start node and goal node, *g (n)* is the actual cost of optimal path between start node and node *(n)* and *h (n)* is the estimated cost between a node *(n)* and the goal node. The lowest calculated *f-value* signifies a safe path with the lowest radiation dose.

New bio-inspired algorithms that originate from mimicking biological behavior are being used to find a near-optimal solution path based on stochastic approaches without constructing complex environment models [33]. For instance, particle swarm optimization (PSO) [35,36] utilizes an objective function obtained at each particle location to determine the best (lowest) function value and the best location. These particles iteratively update their velocities and positions as shown in equations (3) and (4), respectively, using the objective function. The optimal path is obtained after iteratively updating the search for feasible paths that terminate when a stopping criterion is reached.

$$v_{k+1} = w_{vk} + c_1 r_1 (Pbest_k - x_k) + c_2 r_2 (gbest_k - x_k) \tag{3}$$

$$x_{k+1} = x_k + v_{k+1} \tag{4}$$

Where v_k is the current velocity of the particles; x_k is the current position of particles, a representative solution to the optimization problem. $Pbest_k$ is the personal best position of the particles, i.e., the best solution encountered by particle thus far. $gbest_k$ is the global best particle; the best solution found by the population. w is the inertia weight, c_1 and c_2 are the acceleration constants and r_1 and r_2 are random numbers uniformly distributed within [0,1]. v_{k+1} is the vector sum of v_k, $(Pbest_k - x_k)$ and $(gbest_k - x_k)$. While $(Pbest_k - x_k)$ is the difference between the current position and the best position the particle has seen so far, $(gbest_k - x_k)$ is the difference between the current position and the best position of the particles' neighbors.

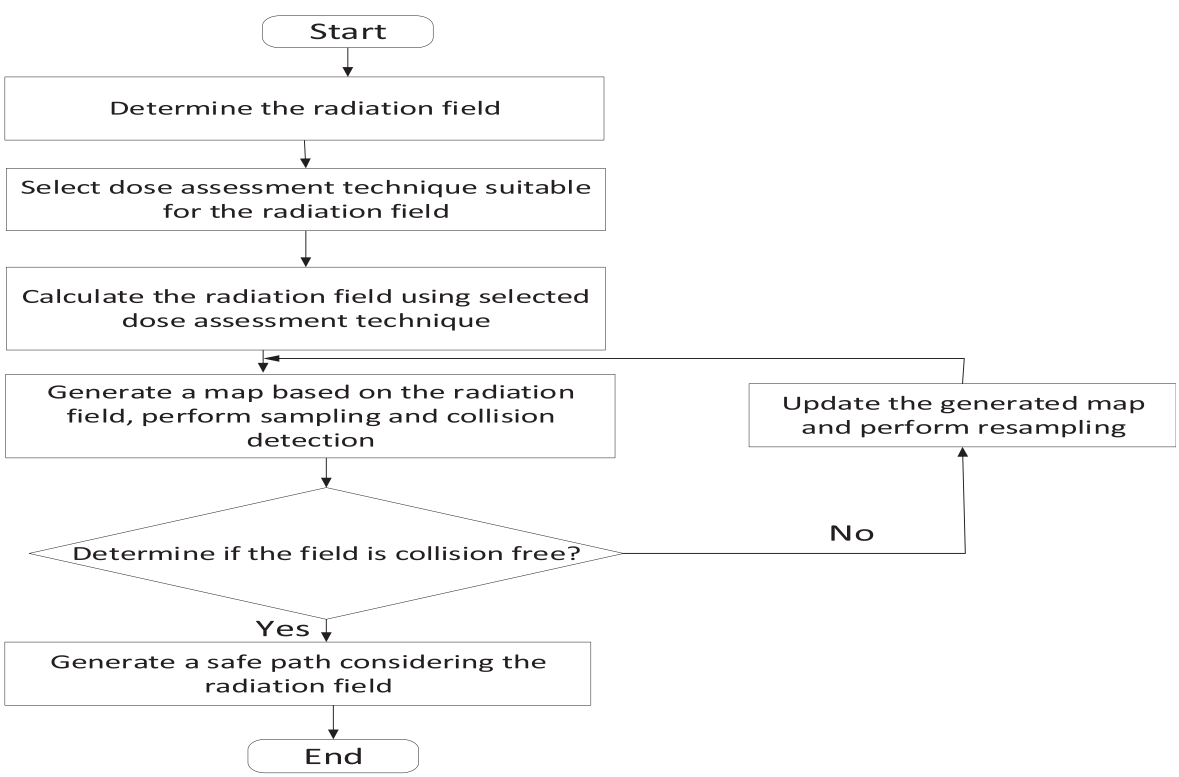

Fig. 1. A flow chart of a typical nuclear facility decommissioning path planning.

The multiapproach technique is sub-divided into two unique parts: real-time, simultaneous multi-approach and ordered multi-approach techniques. While the former combines several algorithms simultaneously to achieve the best results, the latter use an ordered principle in which each algorithm works in a stepwise, separate level [33]. For decommissioning, the simultaneous multi-approach model is commonly applied.

The different path planning algorithms discussed above have been theoretically applied through simulation experiments to solve path optimization problems in nuclear decommissioning field. Liu et al. [37] utilized the A* algorithm with a grid model to design a path in a nuclear facility. The solution depends on the resolution of the grids obtained. This modified A* technique performed better when integrated with the grid model than the conventional graph-based A* algorithm.

Besides, Liu et al. [38] also planned a path for workers applicable in multiple radiation areas to find a minimum dose path by adopting the A*, grid model, segmented path planning, and multiple area modeling. This technique, termed Static Minimum Dose Path (SMDP) method, proved effective, solves the local optimal problem, and finds an optimal solution in multiple radiation areas. However, it may be ineffective in a dynamic environment as seen during nuclear decommissioning.

Liu et al. [31] developed an Improved Particle Swarm Optimization algorithm (IPSO) by combining the merits of PSO and GA algorithms with the multi-objective decision-making approach to generate a path in a nuclear facility. The method can solve both single and multi-objective path planning problems in both discrete and continuous static fields. Wang and Cai [36] developed the Chaotic PSO, (CPSO) with a new mathematical dose model. The error in the cumulative dose is reduced compared with the IPSO developed by Liu et al. The best path obtained also depends on the number of iterations. Wang and Cai [34] proposed PRM*, a technique established by combining PRM and A* algorithms to generate a feasible and safe path for workers. This method produces a path in which the cumulative dose is close to the minimum dose, especially useful in accident situations compared to the A* algorithm.

The inherent weakness of the techniques described above is that they are applied to the static environment without considering the dynamics observed during nuclear decommissioning. To evaluate a dynamic environment, Li et al. [39] utilized the SMDP [38], with a different search strategy for dynamic environment. This technique, called Dynamic Minimum Dose Path (DMDP), is continuously updated as the radiation source changes or obstacles change location. The DMDP depends on the SMDP to search for an optimal path in a changing environment. This implies that a less efficient result in the SMDP will affect the results obtained in DMDP. Furthermore, Chao et al. [3] utilized the RRT* algorithm to plan a path in both discrete and continuous radiation fields to generate an optimal path with minimum dose without relying on the pre-designed road network. Compared with Dijkstra's algorithm, this method proved to be reliable in obtaining smoother and shorter paths in a dynamic environment.

Chao et al. [6] established the BT-RRT* technique by integrating node cost updating, biased path areas sampling and branch-and-bound strategies into T-RRT* to obtain faster and more accurate results in generating a path with a minimum dose. This algorithm converges faster than T-RRT* because of its added advantage of biased path areas sampling that focuses on sampling more on the current optimal path. This reduces the search time for finding an optimal path. Also, Chao et al. [7] developed GB-RRT*, a technique that combined the merits of RRT* with that of the grid search strategy. This method proved to be more reliable, faster, and effective in complex sparse, cluttered, and narrow areas compared to RRT*. However, the walking speed was not considered as it was assumed constant, which changes especially for a dynamic environment for which the algorithm was developed.

Finally, on path planning methods developed for a dynamic environment, Chao et al. [5] established the DL-RRT* technique that combines the merits of D* Lite (a re-planning algorithm) with that of RRT* to generate a minimum dose path for workers. The attribute possessed by DL-RRT* is possible because of asymptotic optimality and probabilistic completeness it inherited from RRT* and the expansion grid search strength and re-planning for the high-quality path it inherited from D* Lite. The algorithm can re-plan quickly as the environment changes by using the previous information gathered, resulting in improved path planning and sampling efficiency. However, the selection of grid resolution affects the performance of DL-RRT*. Table 1 shows the different path planning algorithms with advantages and disadvantages for nuclear decommissioning facilities.

2.2. Multi-path planning

Multi-path planning entails creating different paths where more than one worker is required to perform a specific task. Multi-path planning can further be categorized based on their function, namely;

I. Cooperative
  - Individual-based
  - Group-based
II. Antagonistic or competitive

The individual-based cooperative multi-path planning generates different paths for each worker, knowing the start and goal positions of the other workers. This is to avoid collision between workers and between workers and obstacles. This requires large memory space and is computationally expensive, as it requires recomputing all paths as the environment changes. These problems can be solved by employing A* and D* Lite algorithms, respectively. Another approach, the group-based cooperative path planning, involves grouping the workers based on a similar start and end positions and then generating a path for a worker in each group since workers in a group have a similar destination. Less memory is required, but the individual information about the workers is neglected. This could result in confusion between workers as to the right of passage. If followed strictly, a worker with no knowledge about each other's destination might collide while avoiding collision with obstacles along the generated path [40,41].

From the literature, no algorithm has been developed for multi-path planning for workers in the decommissioning field. However, many approaches have been proposed in robotics, with three algorithms already implemented [41]. The cooperative category can be applied in a decommissioning facility, since some measure of cooperation may be exhibited by workers while carrying out their tasks, to minimize workers' radiation exposure. The antagonistic approach would be counter-productive in the decommissioning environment. This is because the generated paths are adversarial, with assumed competition between workers. The multi-path planning may be sub-optimal in decommissioning since cooperation among workers is needed. Fig. 2 shows a representation of the various path planning algorithms developed for decommissioning facilities.

Table 1
Path planning algorithms in nuclear decommissioning.

Path-planning techniques		References	Advantages	Disadvantages
Graph search	Dijkstra	[26,27]	Capability to obtain a resolution-optimal solution	Gets trapped in local optimal solution; computationally expensive
	A*	[28]	Efficient in narrow areas and environments cluttered with obstacles	High grid resolution guarantees optimality; consumes time in complex and large environments Efficiency might be poor in some cases, limiting the search area and setting allowable deviations improve efficiency
	Modified A*	[37]	Improved convergence speed, faster compared to A*	
	SMDP	[38]	Solves the problem of the local optimal solution, applied in multiple radiation areas	Becomes inefficient as the environment becomes complex and dynamic
	DMDP	[39]	Efficient as it continuously updates to generate a safe path as environment changes	Inaccurate sometimes due to lack of real-time dose simulation calculation
	RRT*	[3]	Capability for a high-quality optimal path that increases with time	Slow convergence, not totally consistent.
	PRM	[24]	Probabilistic completeness, less complex computation in continuous space	Consumes a lot of time especially in a complex environment selected
Multi approach	PRM*	[34]	Faster, cumulative dose close to minimum dose compared to A*	Longer distance for workers to walk for the minimum dose (safe) path generated compared to the safe path obtained
	IPSO	[31]	Improved convergence speed, no local optimal solution	Best results depend on the number of iterations and particles
	CPSO	[36]	Less error even with a large number of nodes, relatively simple and reduced cumulative dose obtained	The early convergence rate is slower compared to PSO
	GB-RRT*	[7]	Converges faster, effective in continuous space with complex obstacles	Walking speed is assumed constant which is not so in reality
	BT-RRT*	[6]	Obtains high-quality minimum dose path in a dense complex environment	Over-optimizes inferior paths, feasible path obtained depends on a large number of samples
	DL-RRT*	[5]	Converges faster, avoids global re-planning	Convergence speed and optimal path generated depends on grid size

3. Algorithm performance evaluation

3.1. The influence of obstacles and configuration space on the efficiency of algorithms

The influence of obstacles and the configuration of a workspace may affect how an algorithm performs. For instance, in Ref. [7], the GB-RRT* algorithm was evaluated in a Cluttered (C) area, Narrow (N) area, and Sparse (S) environments, as shown in Fig. 3. Comparing the performance of the GBRRT* algorithm in the three different environments, the result indicates that the algorithm performed best in an environment with sparse obstacles. In such an environment, the algorithm can make great choices in search of an optimal path. This is possible as it has a good measure of configuration space to plan a route. With sparse obstacles scattered in such an environment, it can sufficiently avoid obstacles while finding a safe path based on the radiation field. The environment cluttered with obstacles also affects the way an algorithm performs. This situation limits the algorithm, as it tries to avoid numerous obstacles while planning an optimal path. The required outcome is to design a route that is also optimal and efficient. However, the dose received by workers in such path will be more than in environments with sparse obstacles.

For a narrow area scenario, the algorithm may be unable to produce an optimum path due to the small configuration space. This results in a sub-optimal algorithm, and paths generated by such an algorithm may not be safe for workers. The GB-RRT* compared with the RRT* shows that the RRT* performs best in an environment with sparse obstacles but performs least in narrow areas. Notwithstanding, the result in Chao et al. [7], affirms that the GB-RRT* algorithm performed better than the RRT* algorithm in the three cases in terms of reliability, convergence, and speed. The gap between the amount of dose received by workers in a narrow area and those obtained by workers in a cluttered and sparse obstacle environment, as revealed in Figs. 3 and 4, reflects how the environment and configuration space can influence algorithm efficiency. By calculating the percentage difference between these algorithms, as shown in Table 2, GB-RRT* S proved to be 15.094% more efficient than GB-RRT* N and 11.321% more efficient than GB-RRT* C. This indicates that workers could receive over 10% more dose if found in a narrow area as opposed to what they could obtain in an environment with sparse obstacles. The RRT* S proved to be 11.921% more efficient than RRT* N and 14.194% more efficient than its RRT* C counterpart. While GB-RRT* C proved to be 4.255% more efficient than GB-RRT* N, RRT* C proved to be 2.581% more efficient than RRT* N. This denotes that algorithms developed for a high-risk environment should be able to perform well regardless of obstacles or size of the area.

3.2. Comparative analysis of common path planning algorithms

The various algorithms proposed for the decommissioning environment shown in Table 1 are either applicable to a static or dynamic environment. This section compares the algorithms based on their performance described in literatures. Although there are variations in experiments used to evaluate their performances, it is worth noting that the analysis in this section is done by considering the assumptions that limit the scope of the evaluations.

The IPSO algorithm developed by Liu et al. [31] utilized dose and distance as its deciding factors to obtain optimal path. Different dose and distance attribute weights result in different optimal paths obtained while successfully avoiding obstacles, as reflected in Fig. 5. The plot reveals that using dose as the main deciding factor; the paths produced are safer as opposed to using the distance as the main deciding factor in obtaining an optimal path. The performance of the algorithm in these two scenarios is compared as

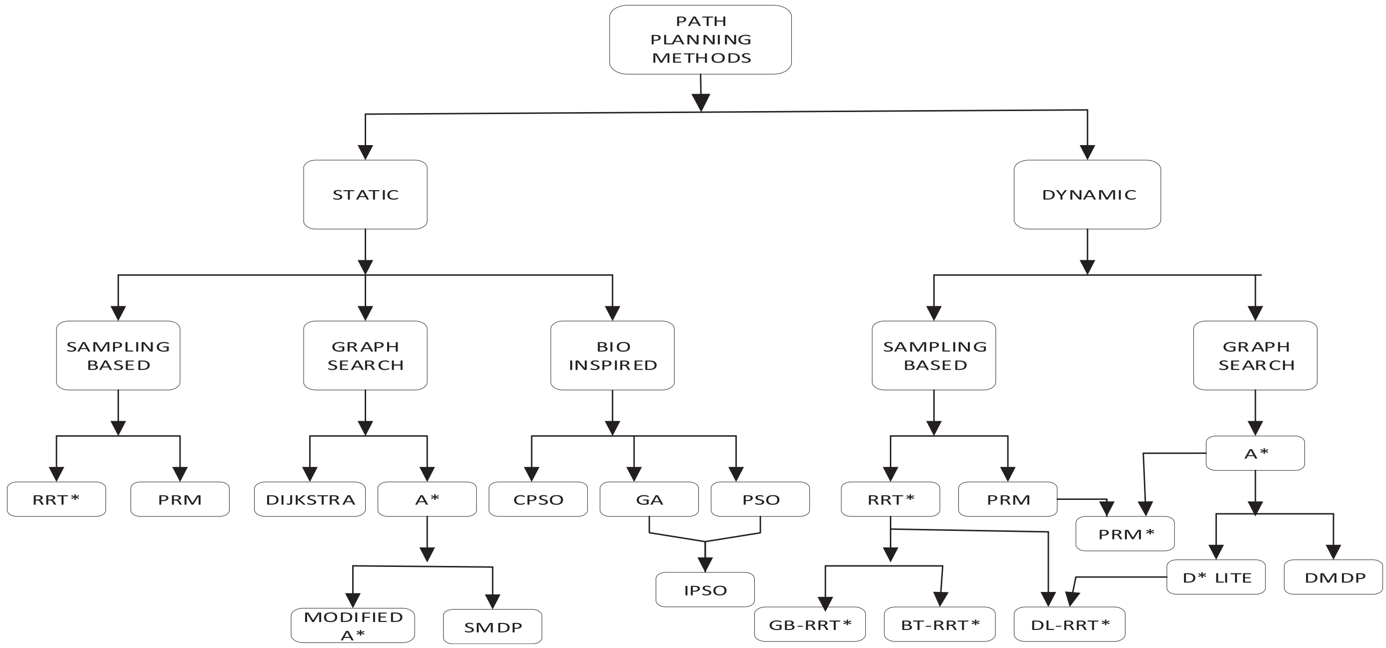

Fig. 2. Multi-approach techniques for developing the path planning algorithm in nuclear decommissioning.

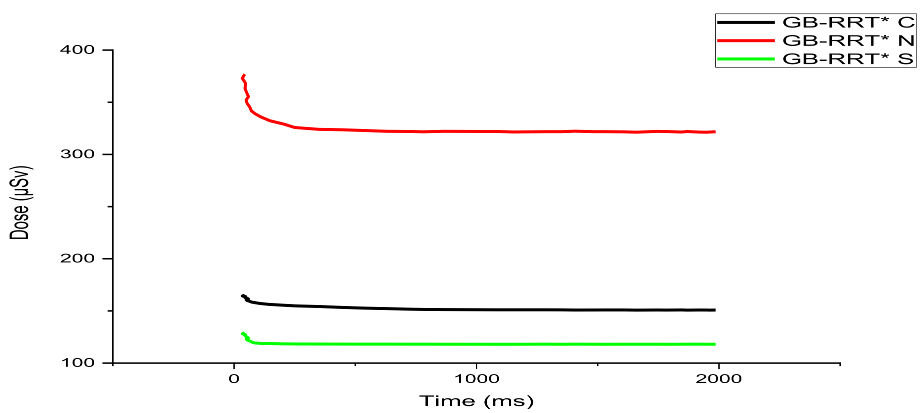

Fig. 3. The influence of obstacles on the performance of the GB-RRT* algorithm in Sparse, Cluttered, and Narrow environments.

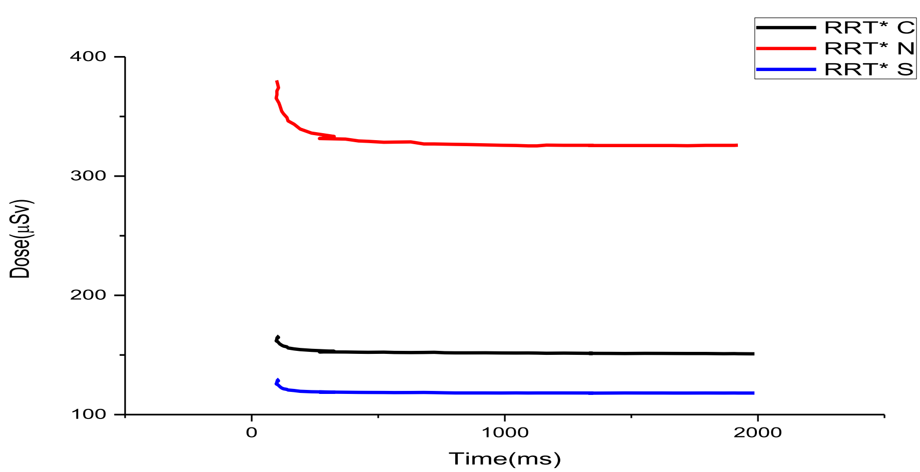

Fig. 4. The influence of obstacles on the performance of the RRT* algorithm in Sparse, Cluttered, and Narrow environments.

Table 2
Performance of GB-RRT* and RRT* in the three environments.

	GB-RRT* S	GB-RRT* C	GB-RRT* N	RRT* S	RRT* C	RRT* N
R^2 Value	0.371	0.329	0.315	0.399	0.465	0.453
% difference	GB-RRT*S VS GB-RRT* C	GB-RRT* S VS GB-RRT* N	GB-RRT* C VS GB-RRT* N	RRT*S VS RRT* C	RRT* S VS RRT* N	RRT* C VS RRT* N
	11.321	15.094	4.255	14.194	11.921	2.581

Table 3
Performance comparison of dose and distance decision factors for IPSO algorithm.

R^2 Value	Dose factor	Distance factor	Modified A*
	0.722	0.782	0.997
% difference	Dose factor Vs Distance factor	Modified A* Vs Dose factor	Modified A* Vs Distance factor
	7.673	27.583	21.565

shown in Table 3. The result shows that when dose is the main deciding factor, the path provided is 7.673% more efficient than that obtained using distance as the main deciding factor. Hence, the IPSO is more efficient when the dose is the main deciding factor in generating an optimal path.

The performance comparison of the modified A* algorithm with IPSO is also shown in Fig. 6 and Table 3. It is observed that for the modified A* algorithm, the dose factor path is more efficient than the distance factor. This further proves the efficiency of paths using dose as the primary decision factor in IPSO over those generated using distance as the main deciding factor.

Moreover, the performance of the CPSO algorithm developed by Wang and Cai [36] was compared with the IPSO. As the number of particles and iterations increases, CPSO can find a better optimal path. Although, the IPSO exhibit early convergence than CPSO, both algorithms essentially get to the optimal value at almost the same number of iterations as shown in Fig. 7. The percentage difference of these algorithms for case 3, with 80 particles, 1200 iterations, with 51 nodes, repeating both algorithms 20 times as shown in Table 4, reveals that the CPSO is 23.551% more efficient than the IPSO. Also, the CPSO converges faster than the IPSO, indicating the better performance of the CPSO over IPSO. The first phase is very significant, as shown in Fig. 7 and the R^2 values obtained for both IPSO and CPSO. The gap in the first phase between IPSO and CPSO is pronounced, thus, it affected the results obtained. Hence, the first phase is considered. This implies that the results obtained largely depend on the number of iterations, which directly indicates the importance of a carefully selected number of iterations. Consequently, the average dose rate value for a discrete field between two nodes may deviate significantly, especially when the distance is considerable. Hence, the whole path was divided into sections and the effective dose of all the sections are calculated and summed.

Moreover, Liu et al. [37], modified the A* algorithm and compared it with the conventional A* algorithm, and the simulation results show that the modified A* is more efficient than the conventional A*. Similarly, Wang and Cai [35] performance comparison shows that the PRM* can find an optimal path with minimum dose but with a longer distance as compared to the A*. The dose rate results from modified A* and PRM* are compared for better analysis, as shown in Fig. 8. The result reveals their performances in finding an optimal path in a static environment. The absorbed dose was used instead of the cumulative dose in Fig. 8, for computational convenience. The relationship between the dose rate and distance has been discussed [37]. [35]. Also, the algorithms are considered in a static environment with the assumption of a constant worker's velocity. Fig. 8 shows the fluctuation in the cumulative dose with distance. The lower dose rate recorded with longer distance is because the dose intensity will reduce at a considerable distance away from the source, reducing the cumulative dose. This is not the case with a short distance, as the dose rate will still be very effective over a short distance, thereby increasing the cumulative dose. Nevertheless, there are scenarios where the cumulative dose could be high even over a long distance, as seen in a continuous radiation field.

The trend in Fig. 8 also shows that the dose rate of the PRM* is significantly lower initially as compared to the modified A*. This results in an optimized path with time as reflected in the low dose rate obtained in the plot for PRM*. There is a rise in the dose rate after a certain distance, although both algorithms converged to almost the same value for a distance greater than 12 m. The percentage difference in the result between the two algorithms is as shown in Table 5. It is also observed that the modified A* algorithm is affected by the heuristic chosen and grid resolution. The heuristic, in this case, was set to zero, further reducing the efficiency of the proposed method especially as the number of points increases. The dose rate obtained by using the PRM* is significantly lower than that obtained using the modified A*. This also agrees with the conclusions of Wang and Cai. In the final analysis, the cumulative dose of the PRM* is significantly lower than that obtained using the conventional A*.

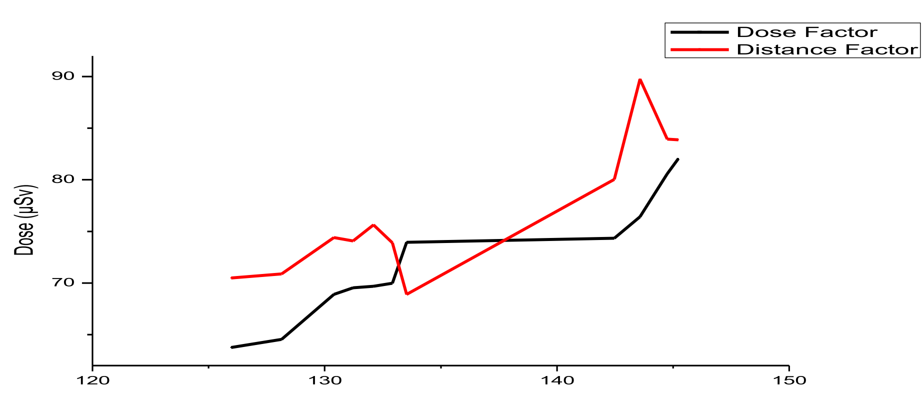

Fig. 5. The influence of the decision factor chosen on the optimal path produced.

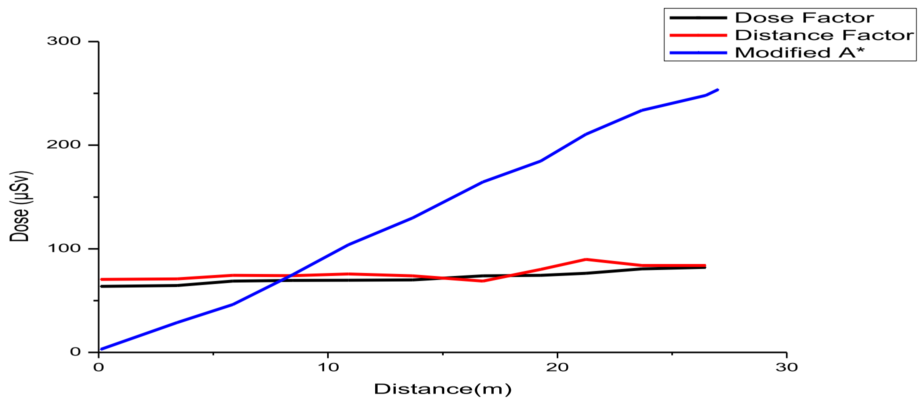

Fig. 6. Performance comparison of Dose factor, Distance factor and Modified A* algorithms.

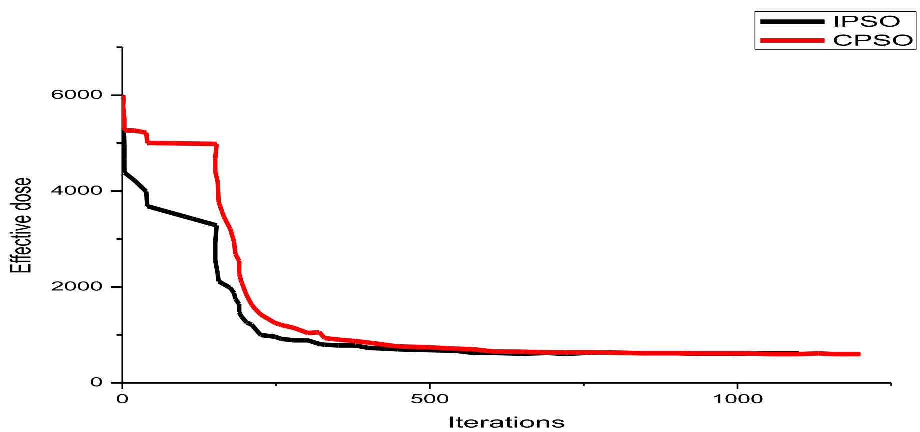

Fig. 7. Path obtained by IPSO and CPSO.

Table 4
Performance comparison of IPSO and CPSO in case 2.

Metric	IPSO	CPSO	% difference
R^2 Value	0.422	0.552	23.551

Table 5
Performance comparison of the Modified A* and PRM*.

Metric	Modified A*	PRM*	% difference
R^2 Value	0.003	0.484	99.380

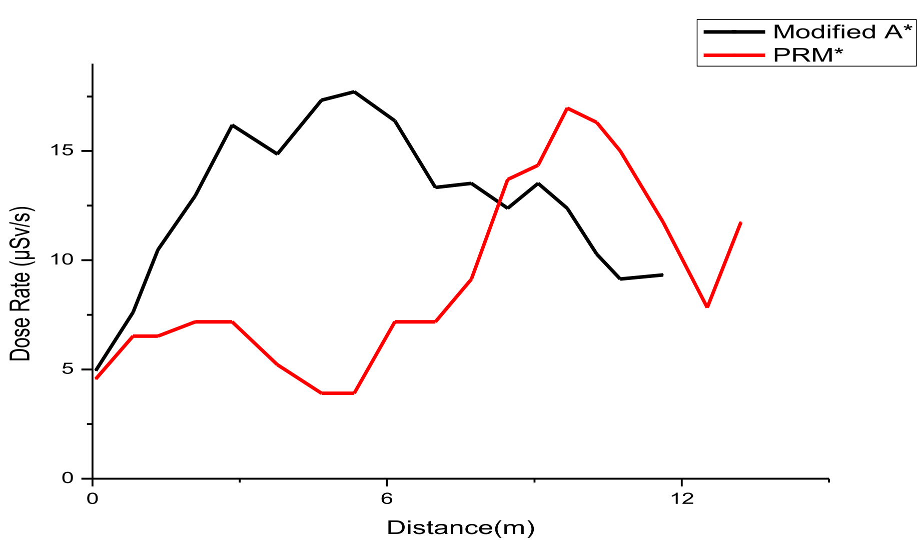

Fig. 8. Dose rate Vs distance plot of the Modified A* and PRM*.

In planning a static environment using SMDP, Liu et al. [38] show that time is also an important deciding factor to be considered. However, this consideration makes it difficult to analyze the algorithm's performance in a dynamic environment. Algorithms such as IPSO, CPSO, Modified A*, and PRM* used distance and dose as the decision factors, and time was not considered a deciding factor.

The RRT* and Dijkstra's algorithm have also been compared by Chao et al. [3] for nuclear decommissioning. The results show that the paths obtained by both algorithms are similar. Besides, the path obtained by RRT* was found to be smoother in an environment with a randomly distributed radioactive source. The results also revealed that the cumulative dose from Dijkstra was higher compared to the value obtained from the RRT*. This shows better efficiency and reliability of the RRT* over the Dijkstra. Moreover, the simulation of the BT-RRT* algorithm proposed by Chao et al. [6] was performed to test the efficiency of BT-RRT* over T-RRT*. The plot of the cost of the best path against time reveals that BT-RRT* converges faster than T-RRT* but in some cases, the cost of the best paths of BT-RRT* was found to be higher than that of T-RRT*.The performances of RRT*, Dijkstra, and BT-RRT* compared in terms of their cumulative doses are shown in Fig. 9. This evaluation shows a clear gap in the efficiency of dose value between the BT-RRT* and those of RRT* and Dijkstra. This is due to the capability of BT-RRT* to focus on sampling in the current optimal path after inheriting the attribute of T-RRT*. BT-RRT* uses biased area sampling, which helps speed up the time used to search for an optimal path since it focuses on sampling in the current optimal path. There are situations where the search could take place in an area far from the optimal path. This may increase the cumulative dose. Similarly, the Dijkstra algorithm is graph-based, and its solution depends on the position of the nodes. As long as there is a uniform distribution of the nodes, the optimal path will be found. When the search for an optimal path is not close to the actual optimal path, the search time is prolonged, resulting in the spike in the cumulative dose seen at 250s.

The attributes combined in BT-RRT* makes the tree near the current optimal path to have higher node density, and as such, BT-RRT* can find the optimal path quickly. This is also a helpful attribute when optimizing the low-dose area, giving the algorithm the ability to plan paths with minimum radiation level as reflected in the cumulative dose obtained using the BT-RRT*. Table 6 shows further analysis of the performance of these three algorithms in a dynamic environment.

Table 6
Performance comparison of the cumulative doses of RRT*, Dijkstra and BT-RRT*.

Metric	RRT*	Dijkstra	BT-RRT*
R^2 Value	0.982	0.986	0.984
% difference	RRT* vs Dijkstra 0.4060	RRT* vs BT-RRT* 0.2033	Dijkstra vs BT-RRT* 0.2028

While BT-RRT* is 0.2028% more efficient than the Dijkstra algorithm in terms of the cumulative dose obtained, it is 0.2033% more efficient than the RRT*. The RRT* on the other hand is 0.4060% more efficient than the Dijkstra algorithm further revealing the superiority of the RRT* over the Dijkstra. The RRT* and BT-RRT* can plan paths without relying on the pre-designed road network which is not the case with the Dijkstra. This makes the Dijkstra algorithm less efficient as the environment becomes dynamic. Hence, for a dynamic environment, it is safer to plan a path using the BT-RRT*. In summary, the BT-RRT* is more efficient for a dynamic environment, followed by the RRT* and lastly, the Dijkstra algorithm.

Another critical factor to be considered is the grid size used in the path planning experiments. The simulation results in testing the performance of GB-RRT* in comparison with the RRT* presented in Chao et al. [7] shows that the GB-RRT* converges faster in different environments compared to RRT*, for a particular grid size. Besides, the GB-RRT* also performs better than the RRT* in narrow and complex environments as RRT* spends much time in performing collision detection for each iteration. Moreover, simulation experiments in Ref. [5]evaluated the performance of DL-RRT* in comparison with RRT* in an environment with moving obstacles and strong shielding material. Results showed that the DL-RRT* produced paths that significantly converge faster than RRT* under the 25 $\times$ 25 grid case. Here, a careful selection of the grid size determines the results obtained using the DL-RRT*. The same trend is observed with the DL-RRT* compared to the RRT* in the case of a radioactive environment with changing radiation sources. Fig. 10 shows the dose plot of common algorithms. The analysis of DMDP [39] was constrained because there are no statistics similar

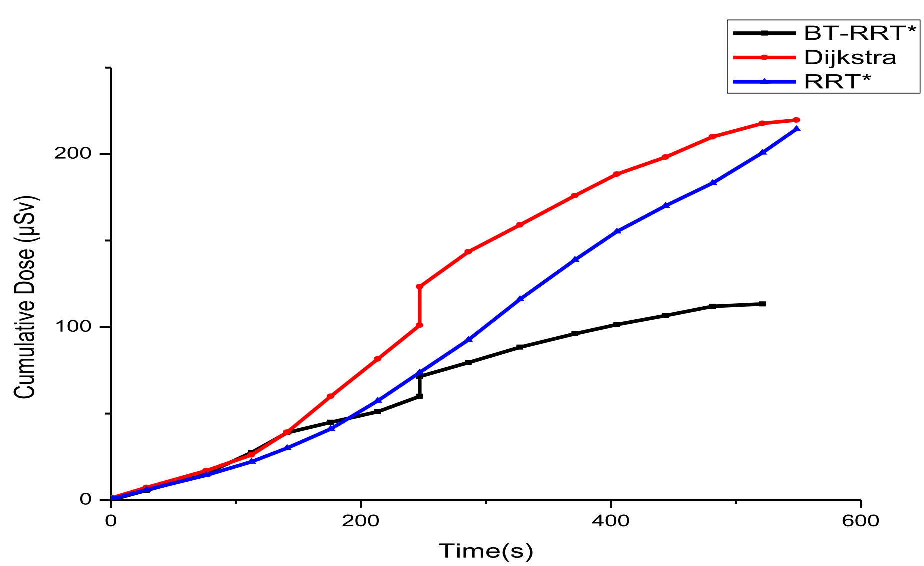

Fig. 9. Cumulative Dose plots of RRT*, Dijkstra and BT-RRT*.

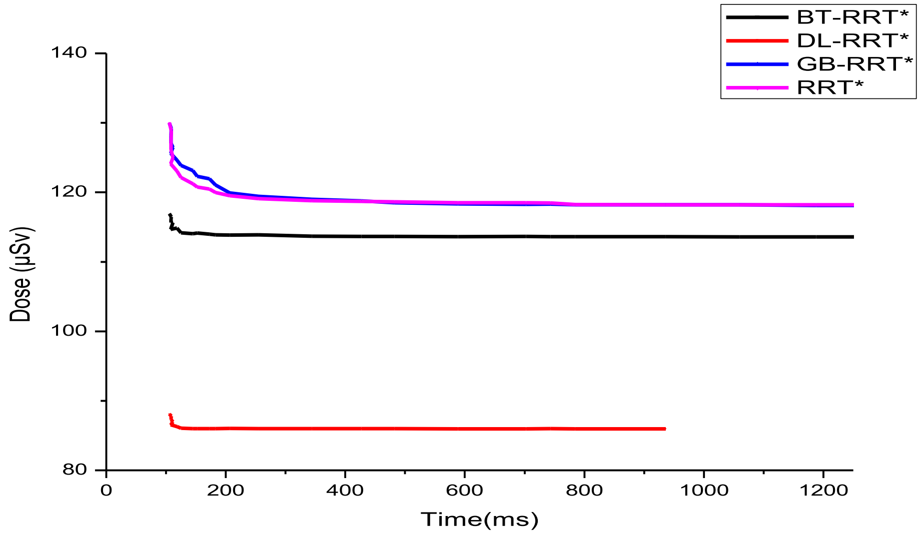

Fig. 10. Dose plots of RRT*, BT-RRT*, GB-RRT* and DL-RRT*.

to the one provided by other dynamic algorithms to aid its comparison.

As shown in Fig. 10, it is evident that the DL-RRT* performs significantly better than the other algorithms for the scenario considered. This clear margin attests to the superiority of the DL-RRT* in specific tasks. The trend of RRT* and GB-RRT* algorithms show a closely related performance. The performance percentage differences presented in Table 7 helps in evaluating their performances against others. The comparison of the performance of the dynamic algorithms reveals that the DL-RRT* is 19.348% more efficient than the RRT*. It is also 11.031% more efficient than BT-RRT*. Also, it is 2.880% more efficient than GB-RRT*. The degree of deviations of DL-RRT* in comparison with the other three algorithms show that it is very efficient as compared to RRT* than it is as compared to BT-RRT*. Its performance comes close to GB-RRT*, as revealed by the percentage deviation between the two algorithms.

We can conclude that DL-RRT* is an effective path-planning algorithm in a dynamic and complex environment. DL-RRT* is also suitable for path re-planning where obstacle and radiation dynamics are considered. The only drawback is that great care is needed to select the grid resolution to get the best results from the DL-RRT*. After the DL-RRT*, the next most efficient algorithm is the BT-RRT* which is 17.556% more efficient than the GB-RRT* and 11.333% more efficient than the RRT*. BT-RRT* focuses on bias path areas sampling, and if the current best path is far from the actual optimal path region, it takes more time in the non-optimal path, thereby increasing cost. However, the next algorithm in terms of performance is the GB-RRT*, which is 7.018% more efficient than RRT* and lastly, the RRT*.

It is worthy of note that the R^2 value is a goodness of fit measure used for comparative linear regression model estimation. Hence, the larger the R^2 values, the better the regression model. However,

Table 7
Performance comparison of RRT*, BT-RRT*, GB-RRT* and DL-RRT*.

Metric	RRT*	BT-RRT*	GB-RRT*	DL-RRT*		
R^2 Value	0.399	0.450	0.371	0.291		
% difference	DL-RRT* Vs RRT* 27.068	DL-RRT* Vs BT-RRT* 35.333	DL-RRT* Vs GB-RRT* 21.563	GB-RRT* Vs RRT* 7.018	BT-RRT* Vs GB-RRT* 17.556	BT-RRT* Vs RRT* 11.333

there are cases where a high R^2 value is not necessarily good, and a low R^2 value may not mean the model is weak. Within the scope of this review, the R^2 values are used to measure the variation in the accuracy of different algorithms. This is important to enable the robust algorithm comparison presented in this work. Further R^2 influencing factors and the effect of various assumptions should be considered to effectively apply the algorithms in different scenarios.

4. Motion planning applications in nuclear decommissioning

4.1. Critical considerations for effective motion planning algorithm application in nuclear facility decommissioning

From the literature reviewed, we observed that advanced path planning research has been conducted in the area of robotics [42] compared with similar research in nuclear decommissioning. Nevertheless, there are similarities in the two fields that could be exploited. That is, with some modifications and additional considerations, advanced algorithms used in robotics can also be applied in nuclear decommissioning. Robots are machines designed to execute one or more tasks repeatedly, with speed and precision. Although human reliability and composition cannot be compared with that of a robot, the similarities inherent and lessons learned in path generation for robots can apply to humans. For instance, Al-Bluwi et al. [43] modified robotic algorithms to suit applications in molecular simulations. Moreover, common techniques such as sampling technique, collision detection against obstacles, and the use of heuristics are being applied in both fields for path planning.

A critical and unique attribute of a nuclear decommissioning environment is the presence of radiation. Consequently, some modifications are required to apply robotic algorithms appropriately. Other constraints worth considerations are the dynamics and kinematic constraints applied to robots for the static and dynamic environment that need to be modified to suit the decommissioning environment for humans, and how to incorporate the trajectory in robotics (a path with the explicit parameterization of time with specifications on velocity, acceleration, jerk, etc) as opposed to a path created for decommissioning. Moreover, for robotics, the turning angle and degree of freedom for the robots, holonomic and non-holonomic drive, and the robotic visual motion planning also need to be modified in the decommissioning environment.

Furthermore, the specification of a given robot will determine the modifications that need to be put in place for its application in decommissioning [44]. The simultaneous localization and mapping (SLAM) algorithm or localization algorithm for a pre-generated map will need to be modified to suit the decommissioning environment [45]. This is because radiation maps are already established for a decommissioning environment and paths are planned based on the generated radiation map. The correct modifications of the algorithm could reduce the time and computational burden present in robotic algorithms since some constraints have been eliminated. This will make the robotic algorithms much easier to be applied to a decommissioning environment.

4.2. Robots for nuclear decommissioning

Currently, advanced research is ongoing to develop robots for nuclear facility decommissioning purposes [46], to reduce clean-up time and cost of disposing of nuclear wastes. These research efforts aim to develop several vast, highly specialized, and advanced algorithms and provide continuous improvement. There is a feasible prospect of integrating the robotic solution into the decommissioning program in the nuclear industry from a cost and safety perspective. The use of robots in a highly radioactive area is not a new concept [44]. There are also situations where the multi-robotic approach was developed for exploration in a highly radioactive area of a storage facility using swarm robots. Exploration is one of the most important bio-inspired behaviors for swarm robotics with many real-world applications, especially in highly radioactive environments. As such, swarm robotics proved to be a more efficient approach to performing tasks when compared to a single robot. The algorithm developed for this task, called the exploration algorithm, was verified in a real environment. These swarm robotic systems also proved to be scalable, as the number of robots deployed could be changed with little or no effect on their overall performances. The system's functions could also be easily modified by selecting an appropriate number of robots, although the real-world application of these techniques could be complex and their developments more tasking [47].

The deployment of robots to undertake tasks in dangerous and high radiation environments is not limited to the ground surface but also applicable in a wet environment such as in the spent fuel pool for inspection and monitoring of wet nuclear storage facilities [48]. For instance, the unique aquatic autonomous surface vehicle (ASV) exhibited localization and tracking accuracy necessary for operation in a wet nuclear storage facility, a task difficult for humans. Also, an autonomous ground-based radiological monitoring robot, called the continuous Autonomous Radiation-Monitoring Assistance (CARMA), was deployed for the first time in an active area at the UK's Sellafield nuclear site, to detect and locate a fixed α source. Robots have also been deployed in Fukushima Daiichi facilities to conduct γ surveys [45]. Worker's safety is paramount during nuclear decommissioning, hence adopting robots to performing some of these tasks [49] will largely shield workers from the harmful effects of radiation. This in effect will reduce full-body dose received by workers. Also, robots will be able to access facilities where human access is restricted due to building configuration. This would improve productivity and reduce human risk. In decommissioning, robots would also be helpful to characterize facilities, including mapping dose rates, identifying materials, and generating topographical maps. The robots would also inspect vessels and infrastructure, move, manipulate, cut, sort, and segregate waste and assist operations staff [50].

Moreover, path planning methods in robotics would utilize fewer iterations to find optimal paths [51]. This would result in a reduction in computation time and increased efficiency. Conventional robots are equipped with velocity profiles and sensors for real-time detection of obstacles, resulting in more flexibility, reduced complexity, and cost. Further, they are not affected by radiation the way humans are, and can perform tasks unsupervised if adequately programmed. With the deployment of robots, there will be less need for work monitoring technologies such as on-site mobile survey system. Also, robots can perform routine tasks nonstop without experiencing fatigue, and robots are not affected by the posture that can influence walking speed. This would eliminate the need for expensive ergonomics: the science of designing a workplace with consideration for the workers' capabilities and limitations.

This prospect of using robots for nuclear decommissioning is attractive. However, the post-decommissioning cleanup cost for the robots, special robot depository for storing the robots, potential radiation transfer from site to robot depository, and robot malfunctions are some factors and events to be considered and managed for effective deployment of robots for nuclear-decommissioning purposes. In case of a sudden loss of control or malfunction, the robots become ineffective. Furthermore, the development of robots capable of implementing decommissioning tasks in a complex nuclear facility would be time-consuming and capital intensive. These issues notwithstanding, the merits outweigh the demerits. If applied in decommissioning, the multi-path planning techniques could ensure more effective decommissioning work, thereby improving productivity. Also, if the multi-path planning techniques are carefully adopted, there will be a considerable increase in decommissioning efficiency and reduced exposure time for workers.

5. Conclusion

In this paper, the various path planning algorithms developed for nuclear decommissioning applications have been reviewed and categorized, with an exhaustive analysis of their advantages and weaknesses. The implementation techniques, decision factors considered and optimization methods are also discussed. The evaluation metrics utilized to measure the performance of the algorithms are also presented. The standard algorithms used for static and dynamic environments are graphically compared, considering the peculiar parameters used in their implementation. As no single technique can be used to solve path planning problems in a highly dynamic environment, recommendations for using hybrid approaches in choosing the dose assessment methods, the sampling techniques, and the algorithms are presented. As a part of future research focus, the various constraints and issues to be considered in adopting motion planning algorithms, and deployment of robots in decommissioning are also discussed.

The effect of obstacles and configuration space on the performance of path-planning algorithms is analyzed, considering specific environments such as sparse, cluttered, and narrow areas. The uniqueness of the DL-RRT* algorithm over others in the radioactive path planning task is discussed and analyzed. Finally, we recommend improved research and development of novel nuclear-decommissioning algorithms that target optimal performance in dynamic environments. This can be achieved by developing algorithms that focus on optimizing the sampling techniques, node adding techniques, and improving heuristics.

Exploring the track of path planning algorithms and research opportunities discussed in this work would accelerate future research efforts toward improved nuclear decommissioning. The algorithm evaluation presented here would also support the research and development of advanced path planning tools and models. The performance comparison of the state-of-the-art algorithms would also aid researchers and decision-makers involved in nuclear-decommissioning projects. This would also support developmental efforts to build better, more reliable, and safer paths in radioactive environments.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research work was funded by Harbin Engineering University. We also acknowledge the technical support project for Suzhou Nuclear Power Research Institute (SNPI) (NO.029-GN-B2018-C45-P.0.99–00003), the Foundation of Science and Technology on Reactor System Design Technology Laboratory (HT-KFKT-14-2017003) and the project of Research Institute of Nuclear Power Operation (No.RIN180149-SCCG).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.net.2021.05.038.

References

[1] S. Rimkevičius, M. Vaišnoras, E. Babilas, E. Ušpuras, HAZOP application for the nuclear power plants decommissioning projects, Ann. Nucl. Energy 94 (2016) 461–471.
[2] R. Storms, S. Walker, Interstate technology regulatory Council - decontamination and decommissioning of radiologically-contaminated facilities guidance - 9118, in: WM2009 Conference, Phoenix, AZ, USA, 2009.
[3] N. Chao, Y.-k. Liu, H. Xia, C.-l. Xie, A. Ayodeji, H. Yang, L. Bai, A sampling-based method with virtual reality technology to provide minimum dose path navigation for occupational workers in nuclear facilities, Prog. Nucl. Energy 100 (2017) 22–32.
[4] G.E. Mathew, Direction based heuristic for pathfinding in video games, Procedia Comput. Sci. 47 (2015) 262–271.
[5] N. Chao, Y.-k. Liu, H. Xia, M.-j. Peng, A. Ayodeji, DL-RRT* algorithm for least dose path Re-planning in dynamic radioactive environments, Nucl. Eng. Technol. (2018) 1–12.
[6] N. Chao, Y.-k. Liu, H. Xia, L. Bai, Minimum dose path planning in complex radioactive environments with sampling-based algorithms, in: 25th International Conference on Nuclear Engineering, Shanghai, China, 2017, pp. 1–7.
[7] N. Chao, Y.-k. Liu, H. Xia, A. Ayodeji, L. Bai, Grid-based RRT for minimum dose walking path-planning in complex radioactive environments, Ann. Nucl. Energy 115 (2018) 73–82.
[8] J.F. Briesmeister, MCNP-A General Monte Catlo N-Particle Transport Code, 2000, p. 790.
[9] A. Ferrari, P.R. Sala, A. Fasso, J. Ranft, FLUKA: a multi-particle Transport code, SLAC-R- 773 (2005) 406.
[10] G. 4, Physics Reference Manual, GEANT 4 Working Group, CERN, 2004.
[11] R. V.G, A. N.A, G. I.O, R. Y.V, Efficiency of the dose rate calculation by Monte-Carlo method and point kernel method when handling radioactive waste, Atom. Energy 114 (2) (2018) 63–69.
[12] C. Devillers, MERCURE 3 Programme., Rapport C. E. A. - R., vol. 3264, Fontenay-aus-Roses, 1967.
[13] MicroShield package. https://en.freedownloadmanager.org/Windows-PC/search/microshield.
[14] V.R. C, The Combinatorial Geometry Version of the QAD-P5a, A Point Kernel Code for Neutron and Gamma Ray Shielding Calculations, 1977.
[15] L.Q. Yang, Y.K. Liu, M.J. Peng, M.K. Li, A gamma-ray dose rate assessment method for arbitrary shape geometries based on voxelization algorithm, Radiat. Phys. Chem. 158 (2019) 122–130.
[16] L.-q. Yang, Y.-k. Liu, M.-j. Peng, M.-k. Li, N. Chao, A Fast Gamma-Ray Dose Rate Assessment Method for Complex Geometries Based on Stylized Model Reconstruction, Nuclear Engineering and Technology, 2019.
[17] N. Chao, Y.-k. Liu, H. Xia, A. Ayodeji, H. Yang, Adaptive point kernel dose assessment method for cutting simulation on irregular geometries in nuclear facility decommissioning, Radiat. Phys. Chem. 150 (2018) 125–136.
[18] I.M. Prokhorets, S.I. Prokhorets, M.A. Khazhmuradov, E.V. Rudychev, D.V. Fedorchenko, Point-kernel Method for Radiation Fields Simulation, 2007.
[19] G. Grand Canyon University, Sampling methods, 2019. https://cirt.gcu.edu/research/developmentresources/research_ready/quantresearch/sample_meth.
[20] R. Song, Y. Liu, R. Bucknall, Smoothed A* algorithm for practical unmanned surface vehicle path planning, Appl. Ocean Res. 83 (2019) 9–20.
[21] P. Jimdnez, F. Thomas, C. Torras, Collision Detection Algorithms for Motion Planning, Institut de Robbtica i Informktica Industrial, Barcelona, 1998, pp. 1–39.
[22] J. Bialkowski, M. Otte, S. Karaman, E. Frazzoli, Efficient collision checking in sampling-based motion planning via safety certificates, Int. J. Robot Res. 35 (7) (2016) 767–796.
[23] Karaman Sertac, F. Emilio, Sampling-based algorithms for optimal motion planning, in: C. Massachusetts Institute of Technology (Ed.), Int. J. Robot. Res., 2016.
[24] K. L.E, P. S, L. J.C, O. M.H, Probabilistic roadmaps for path planning in high dimensional configuration spaces, IEEE Trans. Robot. Autom. 12 (4) (1996) 566–580.
[25] L.E. K, M.N. K, J.C. L, Analysis of probabilistic roadmaps for path planning, IEEE Trans. Robot. Autom. 14 (1) (1998) 166–171.
[26] A.-Q. Alzalloum, Application of Shortest Path Algorithms to Find Paths of Minimum Radiation Dose, University of Illinois, Urbana-Champaign, 2009, p. 139.
[27] D. E.W, A note on two problems in connexion with graphs, Numerische Mathematik 1, 1959, pp. 269–271.
[28] P.E. Hart, N.J. Nilsson, B. Raphael, A formal basis for the heuristic determination of minimum cost paths, IEEE Trans. Syst. Sci. Cybern. 4 (2) (1968) 100–107.
[29] R. Glasius, A. Komoda, S.C.A.M. Gielen, Neural network dynamics for path planning and obstacle avoidance, Neural Network. 8 (1) (1995) 125–133.
[30] S. Mirjalili, J. Song Dong, A.S. Sadiq, H. Faris, Genetic Algorithm: Theory, Literature Review, and Application in Image Reconstruction, Studies in Computational Intelligence, 2020, pp. 69–85.
[31] Y.-k. Liu, M.-k. Li, C.-L. Xie, M.-j. Peng, F. Xie, Path-planning research in radioactive environment based on particle swarm algorithm, Prog. Nucl. Energy 105 (2014) 184–192.
[32] M. Dorigo, C. Blum, Ant colony optimization theory: a survey Theoretical, Comput. Sci. 344 (2005), 243278.
[33] L. Yang, J. Qi, D. Song, J. Xiao, J. Han, Y. Xia, Survey of robot 3D path planning algorithms, Contr. Sci. Eng. (2016) 1–23.
[34] Z. Wang, J. Cai, Probabilistic roadmap method for path-planning in radioactive environment of nuclear facilities, Prog. Nucl. Energy 109 (2018) 113–120.
[35] J. Kennedy, R. Eberhart, Particle Swarm Optimization, International Conference on Neural Networks, IEEE, Perth, WA Australia, 1995, pp. 1942–1948.
[36] Z. Wang, J. Cai, The path-planning in radioactive environment of nuclear facilities using an improved particle swarm optimization algorithm, Nucl. Eng. Des. 326 (2018) 79–86.
[37] Y.K. Liu, M.K. Li, C.L. Xie, M.J. Peng, S.Y. Wang, N. Chao, Z.K. Liu, Minimum dose method for walking-path planning of nuclear facilities, Ann. Nucl. Energy 83 (2015) 161–171.
[38] Y.K. Liu, M.K. Li, M.J. Peng, C.L. Xie, C.Q. Yuan, S.Y. Wang, N. Chao, Walking path-planning method for multiple radiation areas, Ann. Nucl. Energy 94 (2016) 808–813.
[39] M.-k. Li, Y.-k. Liu, M.-j. Peng, C.-l. Xie, S.-y. Wang, N. Chao, Z.-b. Wen, Dynamic minimum dose path-searching method for virtual nuclear facilities, Prog. Nucl. Energy 91 (2016) 1–8.
[40] D. Silver, Cooperative Pathfinding, University of Alberta, Edmonton, Canada, 2005.
[41] T. Standley, R. Korf, Complete algorithms for cooperative pathfinding problems, in: International Joint Conference on Artificial Intelligence, University of California, Los Angeles, 2011, pp. 668–673.
[42] M.G. Mohanan, A. Salgoankar, A survey of robotic motion planning in dynamic environments, Robot. Autonom. Syst. 100 (2018) 171–185.
[43] I. Al-Bluwi, T. Simeon, J. Cortes, Motion planning algorithms for molecular simulations: a survey, Comput. Sci. 6 (2012) 125–143.
[44] I. Tsitsimpelis, C.J. Taylor, B. Lennox, M.J. Joyce, A review of ground-based robotic systems for the characterization of nuclear environments, Prog. Nucl. Energy 111 (2019) 109–124.
[45] B. Bird, A. Griffiths, H. Martin, E. Codres, J. Jones, A. Stancu, B. Lennox, S. Watson, X. Poteau, Radiological monitoring of nuclear facilities using the continuous autonomous radiation monitoring assistance (CARMA) robot, in: IEEE Robotics & Automation Magazine, 2018, pp. 1–10.
[46] W.N. News, Robots get smarter to help with decommissioning, 2018. http://www.world-nuclear-news.org/WRRobots-get-smarter-to-help-with-decommissioning-0405184.html.
[47] X. Huang, F. Arvin, C. West, S. Watson, B. Lennox, Exploration in Extreme Environments with Swarm Robotic System, IEEE International Conference on Mechatronics, Germany, Ilmenau, 2019, pp. 1–6.
[48] K. Groves, A. West, K. Gornicki, S. Watson, J. Carrasco, B. Lennox, MallARD: an autonomous aquatic surface vehicle for inspection and monitoring of wet nuclear storage facilities, Robotics 8 (47) (2019) 1–17.
[49] R. Bogue, Robots in the nuclear industry: a review of technologies and applications, Ind. Robot 38 (2) (2011) 113–118.
[50] U. UK, Research and Innovation, Robotics and Artificial Intelligence for Nuclear, RAIN, 2019. https://gtr.ukri.org/projects?ref=EP%2FR026084%2F1.
[51] M. Nazarahari, E. Khanmirza, S. Doostie, Multi-objective multi-robot path planning in continuous environment using an enhanced genetic algorithm, Expert Syst. Appl. 115 (2019) 106–120.