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A novel sequential block path planning method for 3D unmanned aerial vehicle routing in sustainable supply chains

Muhammad Ikram [a,*], Robert Sroufe [b]

[a] School of Business Administration, Al Akhawyan University in Ifrane, Avenue Hassan II, P.O. Box 104, Ifrane 53 000, Morocco
[b] Falk School of Sustainability & Environment, Chatham University Eden Hall Campus, Gibsonia, PA, USA

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ABSTRACT

Managing sustainable supply chain operations in dynamic three-dimensional (3D) environments is a significant challenge. Unmanned Aerial Vehicles (UAVs) offer transformative solutions to supply chains. This study aims to enhance sustainable supply chain management by considering new opportunities for optimizing UAV networks. The primary objective is to develop advanced path planning and routing algorithms that improve the quality of service in a supply chain. We present a novel Sequential Block Path Planning (SBPP) method, a modified version of the heuristic D* Lite algorithm, to achieve the shortest logistics path with reduced computation time. We utilize queuing theory for task scheduling and UAV assignments within a supply chain network while ensuring efficient and effective task distribution. The results demonstrate that the proposed combination of routing and path planning algorithms significantly improves performance in 3D environments, resulting in shorter logistics paths, enhanced quality of service, and reduced computation time. The outcomes of this study represent a substantial contribution to UAV network management, particularly in terms of efficiency and operational effectiveness. The novel approach utilized in this study contributes to the emerging UAV field in supply chains and enhances sustainability and operational efficiency in logistics networks.

1. Introduction

Supply chain routing, a critical challenge in logistics, involves the strategic planning of product movement from suppliers to customers through optimal transportation routes. This becomes increasingly complex as organizations strive to enhance efficiency and responsiveness in dynamic and uncertain environments. In parallel, path planning and routing for unmanned aerial vehicles (UAVs) address these complexities. It is focused on allocating services to UAVs within the network and determining the shortest path by the present coordinates to several possible designated coordinates of the operational framework [12]. As new task requests are generated in real-time, the dynamic nature of the environment demands path-planning algorithms that guarantee performance.

Under such uncertain conditions, adapting to real-time changes are essential for supply chain and UAV operations. Moreover, specific uncertainties affecting UAV operations in the supply chain include weather conditions such as wind, rain, and poor visibility, which can disrupt flight stability and timing. Obstacles like buildings, trees, and sudden air traffic can force UAVs to alter their routes [49]. Further, dynamic changes in demand, shifting delivery priorities, and fluctuating resource availability can create operational inefficiencies, requiring UAVs to adapt in real-time to ensure timely and efficient deliveries [50]. These variables introduce significant challenges in maintaining consistent and reliable supply chain operations. The obstacle detection sensors mounted on UAVs play a crucial role by continuously identifying obstacles as the UAV progresses toward its destination [28]. If the original path becomes impractical because of newly discovered obstacles, the UAV must swiftly recalibrate its route to avoid collisions. This real-time path adaptation is vital, particularly in scenarios where the destination may shift, ensuring that the UAV remains on the most efficient path and minimizes deviations from its intended route [45].

Although path planning in two-dimensional (2D) space is a thoroughly researched area with a variety of established solutions, such as potential field methods, visibility graphs, and heuristic planning techniques such as the A* algorithm, the unique challenges UAVs present have spurred significant research and innovation. Owing to their flexibility and ability to navigate complex environments, UAVs have recently become increasingly central in fields such as aeronautics [43]. This has led to the development of diverse UAV path planning algorithms,

* Corresponding author.
E-mail address: i.muhammad@aui.ma (M. Ikram).

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categorized into traditional, intelligent, and fusion approaches. They aim to design flight paths that minimize comprehensive costs, such as the risk of destruction, and meet specified performance requirements. Moreover, the application of UAVs extends beyond logistics to include critical roles in remote sensing and geospatial technology. We can see this in managing humanitarian crises and supporting aid efforts. Integrating UAV technology into supply chain operations promises a transformation in how goods are delivered in increasingly automated and precise manners. This integration can be found in the convergence of supply chain logistics and innovative aerial routing solutions [36].

There are typically three problems associated with existing path planning methods. These problems make them less desirable for 3D path planning, an increasingly relevant aspect of contemporary supply chain management. The pioneer algorithms for path planning were initially designed to work offline in known environments, prioritizing accuracy over runtime efficiency [17]. These methods are intended mainly for 2D environments and, as such, struggle to adapt to the complexities of 3D terrains, which are becoming more common in today's supply chain networks, which span various geographies and require dynamic routing solutions [62,63]. Additionally, these algorithms cannot update paths in real-time to accommodate unexpected environmental changes. However, this can be a critical feature for ensuring the robustness of supply chains against disruptions. Finally, they also do not leverage prior information effectively to expedite the search process when recalculating paths. This is essential for optimizing logistical operations. Next, we must understand why UAVs are gaining attention in supply chain management.

Prior studies have divided existing UAV path planning algorithms into three categories: traditional algorithms, intelligent algorithms, and fusion algorithms [8,26,69]. UAVs have gained significant attention and research attention because of their enhanced maneuverability and flexibility, making them suitable replacements for manned aircraft in complex environments. Developing suitable path-planning algorithms for UAVs in complex and changing environments is essential for enhancing supply chain resilience and efficiency [33]. Furthermore, the use of geospatial technologies in humanitarian efforts has expanded significantly, particularly in remote sensing for refugee and internally displaced person populations [16]. In recent years, geospatial technologies have played a crucial role in addressing access to and assisting in humanitarian efforts. The versatility and agility of UAVs can be practical tools in both complex logistical applications and humanitarian missions, highlighting their dual utility in advancing supply chain solutions, i.e., social goods. This helps broadly align attributes of the United Nation's Sustainable Development Goals (SDGs) [13,30] and helps enable environmental, social, and governance, in contemporary terms this is shortened to ESG management across business functions as part of integrated management [58].

In supply chain management, real-time operation and adaptability to dynamic environments can be crucial for maintaining efficient and more sustainable logistics networks. Based on heuristics, incremental planning algorithms such as D* Lite enhance adaptability by building upon the A* algorithm to incorporate previously gathered information. Compared with conventional systems, it takes less time to find multiple short locations [59]. This is particularly advantageous in managing supply chain activities, where the rerouting of logistics vehicles based on real-time data can lead to significant gains in efficiency [19]. Although these algorithms, which are well suited for smaller environments, have shown promise in specific contexts, their application to large-scale 3D maps, typical of supply chain scenarios, has been less than optimal. This is typically due to the computational complexities introduced by the increased number of possible movements.

Recognizing computational demands due to multidimensional environments is an important path planning practice. In a 2D grid, a node may have a maximum of 8 neighboring nodes, whereas in a 3D grid, a node can have up to 26 successor nodes, leading to a significant escalation in computational demands during pathfinding [48]. Supply chains can benefit from 3D routing because they allow for more flexible and intricate paths to maximize storage and minimize transport times within warehouses, distribution centers, and last-mile delivery.

In this study, we build on path-planning algorithmic practices to introduce optimized queuing theory as an application for vehicle routing in supply chains. Doing so offers a policy-driven approach rather than fixed predefined paths. It allows for the evolution of routes as a function of real-time task request inputs, optimizing the overall performance and handling the dynamic nature of supply chain tasks. As a contribution to a growing field of research, in this study, we use a SBPP method as a novel technique for 3D path planning within a supply chain framework. This approach has yet to be applied by other researchers in this context, and the SBPP method, as an advancement of the heuristic D* Lite algorithm, is designed specifically for 3D environments, enabling supply chain efficiency.

Our methodology begins by segmenting the environment into large blocks and simplifying the 3D space into manageable segments, such as breaking the supply chain into distinct logistical segments. These blocks, akin to different stages in the supply chain, are then analyzed and combined if they are free of obstacles, similar to streamlined supply chain processes. A modified D* Lite algorithm is next used to chart a preliminary path between these blocks, mirroring the strategic planning of internodal supply chain routes. The shortest path is determined within each block, reflecting the optimization of individual segments within the broader supply chain.

This process is repeated in the event of newly introduced obstacles, which, in supply chain terms, could represent sudden changes in inventory levels, demand spikes, or logistic disruptions. By employing this methodology, this study makes significant advancements in the efficiency and improved supply chain management sustainability. Its contribution is in its ability to adapt and recalibrate in response to real-time changes, ensuring logistics operations remain resilient and agile.

The structure of this paper is organized as follows. Section 2 provides a literature review on queueing theory and path planning. Section 3 explains the theoretical principles used in routing and path planning. Section 4 details the methodology for developing 3D UAV sustainable supply chain routing via path planning, SBPP, and queueing theory. Here, we create a system model and problem statement, apply queueing theory to the proposed model, and introduce the SBPP method. Section 5 describes the implementation of the proposed method and presents the results. Finally, the conclusion and future recommendations are presented in the last section.

2. Literature review

Integrating UAVs into supply chain operations represents a significant leap forward in logistics and supply chain management. This transformation is driven by the need for enhanced efficiency, responsiveness, and flexibility in managing complex supply chains, particularly within dynamic and uncertain environments [22]. Recent studies underscore the multifaceted impact of UAV technology on supply chain integration, highlighting both the benefits and inherent challenges.

One area of focus in the literature is the impact of digital technologies on supply chain coordination strategies. Bejlegaard et al. [6] examined how end-to-end business intelligence and digital integration enhance operational efficiency and product delivery performance in small-to-medium enterprises (SMEs). Their findings suggest that digital transformation enables more effective coordination across supply chain operations, positioning UAVs as important tools for logistics and delivery tasks. This transformation, facilitated by integrating sales, product development, and production preparation operations, mitigates traditional trade-offs between cost efficiency, product variety, and lead time, significantly improving overall supply chain efficiency [6]. Moreover, Yu et al. [64] explored the effects of environmental scanning on operational performance through supply chain integration and responsiveness. Using the scanning interpretation action performance model and organization information processing theory, they demonstrated that integrating UAVs into supply chain operations can enhance responsiveness to environmental changes, thus improving overall performance. The study's empirical results indicate that environmental scanning positively impacts supply chain integration and supply chain responsiveness, serving as a partial mediator of supply chain operational performance and a full mediator between supply chain integration and operational performance. This research highlights the critical role of supply chain integration as a mechanism for interpreting environmental scanning signals, which is essential for the dynamic adaptation of supply chains utilizing UAVs.

The literature also underscores the importance of supply chain collaboration and performance. Mustafa Kamal, Irani [47] provide a comprehensive review of the factors driving and inhibiting supply chain integration, emphasizing the role of collaborative approaches in enhancing supply chain performance. UAVs can facilitate real-time data sharing and coordination, significantly improving the agility and resilience of supply chains. By leveraging UAV technology, supply chains can achieve better integration and performance outcomes, thus fostering more efficient and responsive logistics operations [5].

Augmented reality (AR) and virtual reality (VR) technologies are also increasingly integrated into supply chain management. Akbari et al. [4] discussed how Augmented reality (AR) and Virtual reality (VR) technologies, when combined with UAVs, can significantly enhance the visualization and monitoring of supply chain activities. The integration of AR/VR with UAVs can lead to more efficient route planning and execution, leveraging the real-time data collection capabilities of UAVs [53]. Adopting AR/VR technologies in supply chain management has helped drive post-COVID-19 recovery efforts [10,11,24].

Khanuja and Jain [32] further explored supply chain integration's enablers, dimensions, and performance outcomes. They highlight that internal and external integration, supported by UAV technologies, can enhance supply chain performance. The study identifies information sharing, process coordination, and strategic alliances as key dimensions of supply chain integration that can be improved using UAVs. These dimensions facilitate more seamless and efficient supply chain operations, underscoring the potential of UAVs in logistics. In addition to logistics and delivery, UAVs are pivotal in other applications, such as remote sensing and disaster response. UAVs with advanced sensors can collect and analyze geospatial data, supporting decision-making in disaster response and resource allocation [15]. Integrating UAVs and geospatial technologies enhances the ability to respond effectively to crises, ensuring timely delivery of aid and supplies [54]. These applications highlight the versatility of UAVs in addressing a wide range of supply chain challenges.

The integration of UAVs has several advantages in terms of performance and efficiency. Zhang et al. [66,67] investigated a hybrid metaheuristic algorithm for optimizing UAV path planning in combat scenarios. Their study demonstrated that hybrid methods can enhance UAV navigation efficiency and adaptability in static and dynamic environments. By optimizing path planning algorithms, UAVs can navigate complex terrains and dynamic conditions more effectively, thereby improving the overall efficiency of supply chain operations [27,29].

Furthermore, the integration of UAVs also plays an increasingly important role in enhancing supply chain resilience. Shishodia et al. [56] provides a review of supply chain resilience, identifying key research areas such as vulnerabilities, capabilities, strategies, and performance metrics. Integrating UAVs into supply chains can increase resilience by enabling real-time monitoring and quick adaptation to changes [55]. The inherent ability of UAVs to navigate complex environments and deliver goods efficiently makes them ideal for dynamic supply chain applications, especially in emerging areas of humanitarian efforts and remote sensing [34]. When UAVs are utilized, supply chains can achieve greater agility and resilience in the face of disruptions.

Despite these advancements, gaps remain in the literature, particularly concerning the development of sustainable UAV-based supply chain routing solutions. Current research typically lacks a more comprehensive approach to modeling that integrates 3D path planning, SBPP, and queuing theory to provide more sustainable and efficient routing solutions. This gap is important to recognize, as most existing models are designed for 2D environments and do not adequately address the complexities of 3D terrains currently encountered in modern supply chains. Furthermore, prior models do not incorporate real-time adaptability to unexpected environmental changes, a feature essential for robust supply chain operations. This study addresses important gaps in the literature by proposing and developing a more comprehensive model for 3D UAV sustainable supply chain routing, integrating path planning, SBPP, and queuing theory. By incorporating these advanced methodologies, this study not only helps optimize logistical operations but also enhances the resilience and sustainability of supply chains. This integrated approach provides a robust framework for real-time adaptation to environmental changes, thus offering a sustainable and efficient routing solution that addresses the limitations of previous models. Fig. 1 presents the UAV sustainable supply chain routing-based framework of the sustainable supply chain.

3. Model development

3.1. Queuing theory

3D UAV sustainable supply chain routing development involves leveraging queuing theory to enhance vehicle routing problems. Researchers have attempted to incorporate vehicle routing problems in the context of queuing theory, introducing an effective routing algorithm that addresses shortcomings in contemporary algorithms, such as a lack of priority and time constraints [25,60]. Traditional queuing theory analyzes network and strategy performance, but UAV routing, formulates a routing plan to provide optimal or suboptimal performance for sequential tasks [2]. The queuing theory for UAV routing has limitations in dynamic environments. However, its combination with dynamic models and other algorithms has been used to solve complex vehicle routing problems, including task priority and time limitations [51]. Bertsimas, van Ryzin [7] introduced queuing theory to solve simple vehicle routing problems without turns, simultaneously providing task location and allocation. More relevant research integrates queuing theory with dynamical models to address complex vehicle routing issues, providing transformation relationships that determine optimal planning parameters such as the number of nodes and operation range. Despite progress, the application of queuing theory to UAV routing remains underexplored, particularly in dynamic environments. In this study, queuing theory-based solutions for UAV routing are developed, dynamic environmental challenges are addressed, and sustainable supply chain solutions that maximize efficiency and minimize environmental impact are emphasized. This more comprehensive approach underscores the potential of sustainable supply chain routing to create efficient, eco-friendly logistics networks.

3.2. 3D path planning

Efficient path planning is essential for UAV missions. In recent decades, research has been conducted to address the path planning problem, but most of this research has focused on 2D environments. However, 2D path planning algorithms often face geometric constraints, high computational costs, and temporal constraints [46,68]. Path planning algorithms are categorized into conventional, cell-based, real-time, and hierarchical methods.

Rapidly-Exploring Random Trees (RRT) is a fundamental conventional method by Lavalle [35] that proposes the shortest path while considering many constraints. Yershova et al. [65] presented a modified RRT named Dynamic Domain RRT. Karaman and Frazzoli [31] built on this prior work while solving the issue of nonoptimal paths by proposing RRT. Despite good performance, RRT lacks optimality in results. Galar

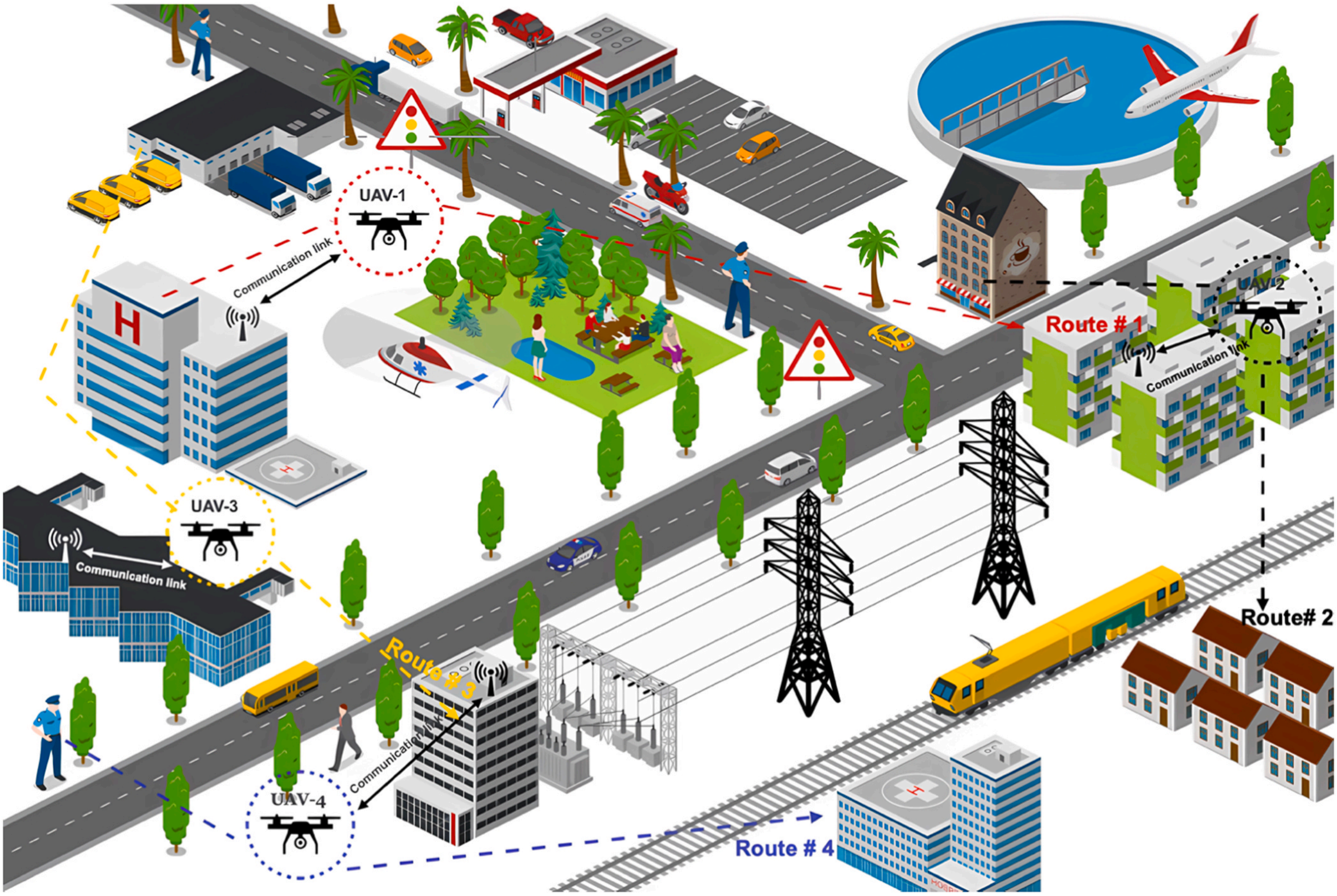

Fig. 1. *:* The framework of UAVs for sustainable supply chain routing.

et al. [23] implemented RRT on mobile robots, which enabled simultaneous UAV navigation. However, it generates a complex network and fails to find the optimal path individually.

Potential field methods achieve obstacle avoidance in which the destination generates attractive forces, whereas obstacles produce repulsive forces [52]. Fang et al. [21] reported that this method, although simple and computationally inexpensive, can generate local minima that trap the UAV. While random noise can remove these minima, it may introduce sharp, unfeasible paths. An isolated planner can provide map connectivity information, which increases the computational cost and is unsuitable for real-time path planning. Liu et al. [42] used a potential harmonic technique to resolve local minima issues caused by potential functions. Ali et al. [3] determined the optimal path via edge and arc weight information, which works well in 2D environments but requires a weighted 3D structure for 3D environments. Furthermore, the A-Star (A*) algorithm has fewer nodes and a heuristic estimation function for cost determination from the current node to the destination node with an octree-based model for UAV networks [39]. Integrating more sustainable supply chain routing into UAV path planning involves leveraging these advanced methods to create efficient, eco-friendly logistics networks. Emphasizing sustainability maximizes efficiency and minimizes environmental impact, ensuring that UAV missions contribute positively to broader supply chain objectives.

3.3. Queueing theory with the M/G/1 model

The queuing model considered in this work is *M/G/1* (where M indicates that the number of tasks arriving is a Poisson process, G indicates that the service times are independently distributed, and 1 is the number of servers). This model is a proven tool for generalizing the solution of Markovian queues for all-purpose task time distributions, making it particularly suitable for 3D UAV sustainable supply chain routing. The applicability of the M/G/1 queuing model can be better clarified by considering a warehouse distribution system in which UAVs are tasked with the delivery of goods. Regarding this particular scenario, the M/G/1 model can adequately depict the stochastic nature of task arrivals and the variable service times driven by factors such as delivery distance and payload [10,11]. In this real-world example, the model demonstrates how it may be utilized to optimize task assignment and eliminate delays throughout the supply chain, hence increasing operational efficiency.

Let us consider a system with *M UAVs* and *T* tasks such that the time between successive task completions has an exponential distribution with intensity $\lambda > 0$. Furthermore, $\bar{t}$ is the time between task arrival and completion, t_w is the waiting time of the task, and $\bar{t}_s$ is the average time of the task distribution. The minimum stability criterion is defined as $\sigma = \lambda\bar{v}$, where σ is the time the UAV spends performing service and where $\bar{v}$ is the mean service time such that $E(v) = 1/\bar{v}$. The response time of a UAV in the M/G/1 queue must be expressed according to the mentioned stability criteria.

Definition 1. Let v_1 and v_2 represent the service times of two UAVs; then,

i. v_1 and v_2 are independent random variables
ii. The cumulative distribution function is defined as $G(x) = P(v_1 \le x) = P(v_2 \le x)$ for all $x \ge 0$

Let Tw_m be the waiting time in a queue of the *m*-th task, $T(t)$ be the number of supply chain pending tasks at time *t*, $T(t_i)$ be the number of pending tasks just before the arrival of task *i*, and $T_r(t)$ be the residual service time in task completion. Let t_m also denote the arrival time of the m-th task for $m \geq 1$ and v_m denote the service time of task m.

The first moment of the waiting time of the i-th task is given as

$$\begin{aligned} E[Tw_i] &= E[T_r(t_i)] + E\left[\sum_{j=i-X(t_i)}^{i-1} v_j\right] \\ &= E[T_r(t_i)] + \sum_{k=0}^{\infty}\sum_{j=i-k}^{i-1} E\left[v_j | T(t_i) = k\right] P(T(t_i) = k) \\ &= E[T_r(t_i)] + \frac{1}{\overline{v}} E[T(t_i) = k] \end{aligned} \tag{1}$$

To find the mean value, let $i \rightarrow \infty$, and Eq. (1) becomes

$$\overline{Tw} = \overline{T_r} + \frac{\overline{T}}{\overline{v}} \tag{2}$$

where $\overline{T_r} = \lim_{i\to\infty} E[T_r(t_i)]$ is the average service time and where $\overline{T} = \lim_{i\to\infty} E[T(t_i)]$ is the average number of tasks in Eq. 2.

According to Little's formula [41],

$$\overline{T} = \lambda \overline{Tw} \tag{3}$$

Substitution of Eq. (2) and the stability criteria in Eq. (3) results in

$$\begin{aligned} &\overline{Tw}(1-\sigma) = \overline{Tr} \\ &\Rightarrow \overline{Tw} = \frac{\overline{Tr}}{(1-\sigma)} \end{aligned} \tag{4}$$

The next step is to calculate the average service time $\overline{Tr}$. Let Tc be the time when the queue is null and O number of tasks completed in $[0, Tc]$. The average service time $\overline{Tr}$ is given as in Eq. (4)

$$\begin{aligned} \overline{Tr} &= \lim_{Tc\to\infty} \frac{1}{Tc} \sum_{m=1}^{O_c} \frac{v_i^2}{2} \\ &= \lim_{Tc\to\infty}\left(\frac{O_c}{Tc}\right) \lim_{Tc\to\infty}\left(\frac{1}{O_c}\sum_{m=1}^{O_c}\frac{v_i^2}{2}\right) \\ &= \lambda \frac{E[v^2]}{2} \end{aligned} \tag{5}$$

where $E[v^2]$ is the second-order moment of the service time at the destination. Using Eq. (4) with the above Eq. (5), we obtain in Eq. (6)

$$\overline{Tw} = \frac{\lambda E[v^2]}{2(1-\sigma)} \tag{6}$$

which is the average waiting time in the M/G/1 queue. Thus, the average time to perform the task is given as in Eq. (7)

$$\overline{t} = \frac{1}{\overline{v}} + \frac{\lambda E[v^2]}{2(1-\sigma)} \tag{7}$$

Additionally, the average number of tasks in the entire queueing system is derived in Eq. (8).

$$\overline{T} = \sigma + \frac{\lambda E[v^2]}{2(1-\sigma)} \tag{8}$$

Since $E[v^2] = 2/\overline{v}^2$, the average waiting time in terms of the stability term is now given in Eq. (9).

$$\overline{Tw} = \frac{\lambda}{\overline{v}^2(1-\sigma)} = \frac{\sigma}{\overline{v}(1-\sigma)} \tag{9}$$

Theorem 1. The average number of tasks at any time in an M/G/1 queueing model is equal to the average number of completed tasks such that for N tasks in Eq. (10)

$$E[N] = \sigma + \frac{\lambda^2 E[v^2]}{2(1-\sigma)} \tag{10}$$

Proof. Let N_m tasks remain after the completion of the m-th task. Additionally, assume that there are L_{m+1} tasks that are received during the completion of the $m+$ *1*-th task. Then, for all $m \geq 1$

$$N_{m+1} = \begin{cases} N_m - 1 + L_{m+1} & \text{if } N_m \geq 1 \\ L_{m+1} & \text{if } N_m = 0 \end{cases} \tag{11}$$

Now, a function Δ_k is assumed with properties (i) $\Delta_0 = 0$ and (ii) $\Delta_k = 1$ if $k \geq 1$. Eq. (11) is modified and rewritten as in Eq. (12)

$$N_{m+1} = N_m - \Delta_{N_m} + L_{m+1}, \quad \forall m \geq 0 \tag{12}$$

To prove Theorem 1, we need to find $E[N]$. Now, we can take the expectation of both sides of Eq. (12) and obtain in Eq. (13)

$$E[N_{m+1}] = E[N_m] - E[\Delta_{N_m}] + E[L_{m+1}], \quad \forall m \geq 0 \tag{13}$$

First, we determine $E[L_{m+1}]$, which is independent of m, as shown below in Eq. (14):

$$\begin{aligned} E[L_{m+1}] &= \int_0^\infty E[L_{m+1} | v_{m+1} = y]\, dG(y) \\ &= \int_0^\infty \lambda y\, dG(y) \\ &= \sigma \end{aligned} \tag{14}$$

For $m \rightarrow \infty$, Eq. (13) can be rewritten as in Eq. (15)

$$\begin{aligned} &E[N] = E[N] - E[\Delta_N] + \sigma \\ &\Rightarrow E[\Delta_N] = \sigma \end{aligned} \tag{15}$$

Now, we can take the square of both sides of Eq. (12) and then the expectation that will result in Eq. (16)

$$\begin{aligned} E\left[N_{m+1}^2\right] = {} & E\left[N_m^2\right] + E\left[(\Delta_{N_m})^2\right] + E\left[L_{m+1}^2\right] - 2E[N_m \Delta_{N_m}] \\ & + 2E[N_m L_{m+1}] - 2E[\Delta_{N_m} L_{m+1}] \end{aligned} \tag{16}$$

As previously discussed, it is clear that $(\Delta_{N_m})^2 = \Delta_{N_m}$ and $N_m \Delta_{N_m} = N_m$ Therefore, we obtain.

$$\begin{aligned} &E\left[(\Delta_{N_m})^2\right] = E[\Delta_{N_m}] \\ &E[N_m \Delta_{N_m}] = E[N_m] \end{aligned} \tag{17}$$

Additionally, from Eq. (15), the following can be derived:

$$\begin{aligned} &E[N_m L_{m+1}] = E[N_m] E[L_{m+1}] = \sigma E[N_m] \\ &E[\Delta_{N_m} L_{m+1}] = E[\Delta_{N_m}] E[L_{m+1}] = \sigma E[\Delta_{N_m}] \end{aligned} \tag{18}$$

Substitution of Eqs. (17) and (18) in Eq. (16) results in

$$E\left[N_{m+1}^2\right] = E\left[N_m^2\right] + E[\Delta_{N_m}] + E\left[L_{m+1}^2\right] - 2(1-\sigma)E[N_m] - 2\sigma E[\Delta_{N_m}] \tag{19}$$

For $m \rightarrow \infty$ and inserting Eq. (15), Eq. (19) can be rewritten as

$$E[N] = \sigma + \frac{\lim_{m\to\infty} E\left[L_{m+1}^2\right] - \sigma}{2(1-\sigma)} \tag{20}$$

Now, we have to determine $E\left[L_{m+1}^2\right] = \int_0^\infty E\left[L_{m+1}^2 | v_{m+1} = y\right] dGy$. First, we find a moment as follows:

$$E\left[L_{m+1}^2 | v_{m+1} = y\right] = E[\text{Numberofpointsinpoisionprocessinregion}(0, y)]$$

$$= e^{-\lambda y} \sum_{k\geq 1} k^2 \frac{(\lambda y)^k}{k!}$$

$$= e^{-\lambda y} \sum_{k\geq 1} k \frac{(\lambda y)^k}{(k-1)!} = e^{-\lambda y} \sum_{k\geq 1} (k-1+1) \frac{(\lambda y)^k}{(k-1)!}$$

$$= e^{-\lambda y}\left(\sum_{k\geq 2}\frac{(\lambda y)^k}{(k-2)!}+\sum_{k\geq 1}\frac{(\lambda y)^k}{(k-1)!}\right)$$

$$= e^{-\lambda y}\left((\lambda y)^2 e^{\lambda y}+\lambda y e^{\lambda y}\right) = (\lambda y)^2+\lambda y \tag{21}$$

Now, we can determine

$$E\left[L_{m+1}^2\right] = \lambda^2\int_0^\infty y^2 dGy+\lambda\int_0^\infty y dGy \\ = \lambda^2 E\left[v^2\right]+\sigma \tag{22}$$

Now, the substitution of Eq. (22) in Eq. (21) provides that

$$E[N] = \sigma+\frac{\lambda^2 E[v^2]}{2(1-\sigma)}$$

This is the proof of Theorem 1. This model, incorporates 3D UAV sustainable supply chain routing, ensures optimal routing and queuing management for efficient supply chain operations via UAVs.

3.4. Modified D* Lite Algorithm

The modified D* Lite is different from D* Lite in that it navigates to locate the neighbor path through the grid's corners, as shown in Fig. 2. It operates by maintaining a set of five distinct values for each node, which include the following: $g(n)$ represents the estimated cost from the destination node to a given node. This cost, typically denoted as $J(n_{dest}, n)$, is usually initialized to infinity. The heuristic is an operator-provided estimate of the cost $J(n, n_{start})$, which must not overestimate the actual cost to be considered acceptable. It also needs to follow the triangle inequality to ensure consistency, which is a necessary condition for finding the shortest path $h(n,n'') \leq h(n,n')+h(n',n'')$. A typical heuristic $h(n, n_{start})$ used when a UAV can move in any direction is the Euclidean distance. The f value represents an estimate of the minimum cost required to travel from the destination to a specific node, defined in Eq. (23):

$$f(n) = g(n)+h(n, n_{start}) \tag{23}$$

The parent node of a given node is identified by its back-pointer, which is represented as $bptr(n) \in succ(n)$. Notably, $succ(n)$ denotes all the successors of a given node. Upon search completion, the shortest path is traced by the back-pointer. Initially, it is set to *NULL* when a node n is encountered, which is calculated via Eq. (24).

$$bptr(n) = \begin{cases} NULL & \text{if } n = n_{start} \\ \text{argmin}_{n'\in succ(n)}(g(n')+J(n',n)) & \text{else} \end{cases} \tag{24}$$

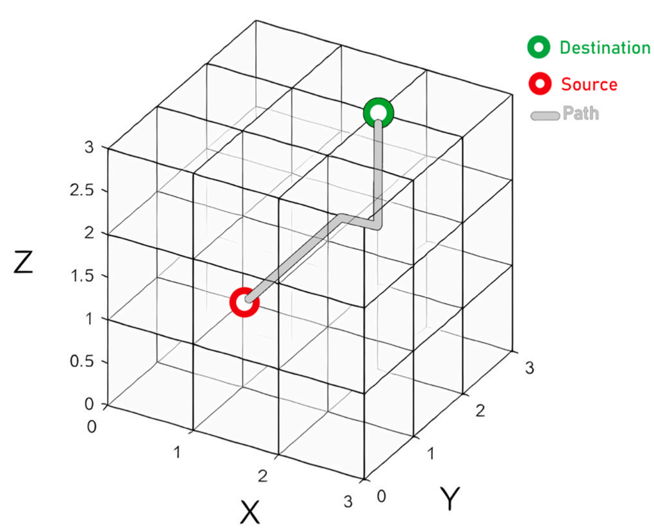

Fig. 2. *:* A typical 3D logistics path through the modified D* lite algorithm.

The right-hand side (rhs) value of a node is based on the g value of $succ(n)$ and must always satisfy Eq. (25). Its value depends on a node's neighbors, making it more knowledgeable than the g value is because it is always one step ahead. A node is said to be consistent if $g(n) = rhs(n)$, inconsistent if $g(n) \neq rhs(n)$, overconsistent if $g(n) > rhs(n)$ and under-consistent if $g(n) < rhs(n)$. Importantly, when $rhs(n) = \infty$, no node will point to n as its minimum cost successor; therefore, $bptr(n) = NULL$.

$$rhs(n) = \begin{cases} 0 & \text{if } n = n_{dest} \\ \text{argmin}_{n'\in succ(n)}(g(n')+J(n',n)) & \text{else} \end{cases} \tag{25}$$

Consistency introduces a change in how the priority queue operates. The queue now holds only the inconsistent nodes whose g values need to be adjusted for consistency. These nodes are sorted lexicographically on the basis of their core points $k(n)$, as demonstrated in Eq. (26).

$$k(n) = \begin{bmatrix} k_1(n) \\ k_2(n) \end{bmatrix} = \begin{bmatrix} \min(g(n), rhs(n)+h(n, n_{start})) \\ \min(g(n), rhs(n)) \end{bmatrix} \tag{26}$$

The initial set U is structured as a priority queue ordered by f values, where the node with the smallest f value is expanded first. Initially, U includes only the starting node n_{dest}. Each of its successors is processed to calculate their respective f values during the expansion of a node. 3D UAV sustainable supply chain routing framework; these modifications to the D* Lite algorithm are critical. The UAVs must navigate complex three-dimensional environments to deliver supplies efficiently [40]. Finding the shortest paths through grid corners ensures optimal routing, which is crucial for minimizing energy consumption and time in supply chain operations. Using consistent heuristics and efficient priority queue management enables UAVs to adapt to dynamic changes in the environment, ensuring reliable and sustainable routing solutions. The Modified D* Lite algorithm's robustness in handling dynamic obstacles and its efficiency in pathfinding make it an ideal choice for UAV-based sustainable supply chain routing.

3.5. Routing and 3D path planning

The proposed routing and path planning algorithm aims to achieve the following objectives: queueing theory proposes a policy to assign tasks to different UAVs in the network. It assigns the task keeping in view to the overall optimized response. In the framework of 3D UAV sustainable supply chain routing, tasks such as deliveries, pickups, and maintenance checks are allocated to UAVs to minimize wait times, balance the workload across the fleet, and ensure timely completion of tasks. The goal is to increase the efficiency and reliability of supply chain operations by effectively managing UAV tasks based on their current states and capabilities.

The SBPP algorithm provides a plan for each UAV to obtain the most efficient way to accomplish all tasks. For 3D UAV sustainable supply chain routing, this involves creating optimal flight paths that consider the three-dimensional nature of the environment. The SBPP algorithm ensures that each UAV follows a route that avoids obstacles, reduces energy consumption, and meets delivery deadlines. By planning efficient paths, the algorithm contributes to enabling the sustainability aspects of the supply chain by reducing the carbon footprint and operational costs associated with UAV logistics. These objectives are important for effectively implementing a 3D UAV sustainable supply chain routing system. The combination of queuing theory and SBPP ensures that UAVs are assigned tasks in an optimized manner and follow the most efficient paths to complete those tasks. This integrated approach leads to a robust and more sustainable supply chain solution capable of adapting to dynamic changes in the environment and maintaining high levels of service performance.

In a close environment Ω with area $\boldsymbol{A}$, it is assumed that there are M UAVs denoted by set $M = \{1, 2, ..., M\}$ and a dynamic process that generates T tasks such that$T = \{1, 2, ..., T\}$. Tasks are generated by a single user and controlled by a central station. The distance between two tasks T_i and T_j is defined as ∂_{ij}, and the distance between a task T_i and a UAV M_j is defined as $\widehat{\partial}_{ij}$. If there are equal or fewer tasks than UAVs, i.e., $T \leq M$. It is also assumed that the time between successive actions has an exponential distribution with intensity $\lambda > 0$ and that tasks are independently and uniformly distributed in Ω. Moreover, UAVs are instantly informed of the arrival of new tasks. The UAV moves at a constant speed ν and has no restrictions on fuel or service capabilities. The time between task arrival and completion is denoted as $\bar{t}$, which is given as

$$\bar{t} = \bar{t}_w + \bar{t}_s$$

where t_w is the waiting time of the task and where $\bar{t}_s$ is the average time of the task distribution. Every task is considered to have an M/G/1 queue. It is assumed that UAVs move within the grid of a 3D environment and provide service to tasks whose information about time, location, and service nature is stochastic and is informed to the UAV when a new task arrives.

The stability of the system is defined as the balance between the number of tasks performed and the number of new tasks; i.e., the number of new tasks should be at least the same rate as the number of tasks performed. Little's law for stability states that $\overline{T} = \lambda \bar{t}_w$[41]. The minimum stability criterion is defined in Eq. (27)

$$\sigma = \lambda \bar{\nu} < 1 \tag{27}$$

where σ is the time the UAV spends performing the service and where $\bar{\nu}$ is the mean service time at the destination. For the average distance $\overline{D}$ traveled per task, the stability condition is defined in Eq. (28).

$$\bar{t}_s + \frac{\overline{D}}{\nu} < \frac{1}{\lambda} \tag{28}$$

This system stability is critical for maintaining a seamless flow of operations. The UAVs must be able to handle the incoming tasks efficiently to prevent backlogs and delays. By adhering to the stability conditions, the supply chain network can ensure that UAVs perform tasks at a rate that matches or exceeds the rate of new task arrivals, thereby maintaining effective and sustainable supply chain operation.

3.6. Queueing theory as routing protocol

It is assumed that UAVs are controlled to fly in an environment Ω at constant speed v alongside a circumscribed curve. More specifically, the instant radius of the curve is limited to be μ or greater [9]. The UAVs are alike and can fly to any destination without any limitations. The problem is simplified by assuming that the environment Ω is a rectangular shape with height h and width w such that $w > h$ and $A = wh$. It is assumed that the UAV does not spend any time at the destination and that $\bar{t}_s = 0$.

Let $D_\mu(m)$ be the distance between a UAV inside Ω and the nearby point among m points that are evenly distributed in the Ω environment alongside the path. The reachability condition states that, for greater values of$m$ is presented in Eq. (29)

$$\overline{D}_\mu(m) = \bar{\alpha}_D \sqrt[3]{\frac{\mu A}{m}} \tag{29}$$

where $\bar{\alpha}_D$ is a constant. For this work, $t_{\bar{s}} = 0$, so the stability requirements can be written in Eq. (30)

$$\frac{\overline{D}_\mu(\overline{T})}{\nu} \leq \frac{1}{\lambda} \tag{30}$$

According to Little's statement, for large values of λ, we have in Eq. (31)

$$\frac{1}{\lambda} \geq \frac{\overline{D}_\mu(\overline{T})}{\nu} \geq \frac{\bar{\alpha}_D}{\nu} \sqrt[3]{\frac{\mu A}{\lambda \bar{t}}} \tag{31}$$

Therefore, the time-limiting condition is obtained in Eq. (32)

$$\bar{t} \geq \bar{\alpha}_D^3 \lambda^2 \frac{\mu A}{\nu^3} \quad \forall \ \lambda \to \infty^+ \tag{32}$$

The routing policy aims to allocate tasks to each UAV such that the tasks are optimally accomplished. Every UAV performs the task with a possible minimum distance. The queuing theory also ensures that one task is not assigned to more than one UAV. The routing policy is stated in the following steps:

First, the intertask distance matrix is calculated. The matrix is defined by means of distance, as the prime objective of the queuing-based routing process is to minimize the travel distance of every UAV. The matrix is recalculated after every task is performed, and each element of the matrix is calculated on the basis of the distance between every task duo. The matrix is defined in Eq. (33).

$$\Gamma(t) = \begin{bmatrix} \ell_{11} & \ell_{12} & \dots & \ell_{1n} \\ \ell_{21} & \ell_{22} & \dots & \ell_{2n} \\ & \dots & & \\ \ell_{n1} & \ell_{n2} & \dots & \ell_{nn} \end{bmatrix} \tag{33}$$

where $\ell_{ij} = \frac{1/\partial_{ij}}{\sum_{i \neq j} 1/\partial_{ij}}$ and$\partial_{ij} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2}$

As the number of tasks is variable, the matrix order is also variable. Notably, $\ell_{ii} = 0$; therefore, the diagonal elements of the matrix are also zero.

After the determination of the interdistance matrix, the state vector of each UAV is calculated. The state vector is defined as the vector with every element as a function of the distance of a UAV with respect to all tasks. The state vector for UAV M_i is defined as

$$V_{M_i}(t) = \begin{bmatrix} \widehat{l}_{i1} & \widehat{l}_{i2} & \dots & \widehat{l}_{in} \end{bmatrix} \tag{34}$$

where $\widehat{l}_{ij} = 1/\widehat{\partial}_{ij}$

After the state vector for each UAV is defined in Eq. (34), the task proximity cost vector of each UAV is calculated. This vector provides the optimality of a UAV with respect to each task, and a value with a lower magnitude has higher optimality. The vector is calculated as the product of the inter distance matrix and the state vector and is defined in Eq. (35) as follows:

$$\widehat{V}_{M_i}(t) = V_{M_i}(t) \times \Gamma(t) \tag{35}$$

The final step in the routing policy is the allocation of tasks in a queue. For m tasks, a queue vector with m elements is formed. Each element is the minimum value of the proximity vector for a particular UAV. If a minimum value corresponding to the task is already taken, then the next minimum value is considered. After a task is performed, all steps are repeated, and the queue vector is also calculated again on the basis of the proximity vector. The queue vector is shown below in Eq. (36):

$$Q(t) = \left\{ q_1, q_2, \dots, q_n, q_i \in \widehat{V}_{M_i}(t) \right\} \tag{36}$$

UAVs can efficiently navigate a three-dimensional environment to perform logistics tasks. They must adhere to the routing policy to minimize travel distances and ensure timely task completion [30].

Algorithms like A* , RRT, and D Lite* are commonly employed in path planning; however, they demonstrate notable limitations when applied to dynamic and uncertain environments. A* is optimal and complete; however, it experiences considerable computational overhead, especially in complex environments, making it less appropriate for real-time applications that necessitate quick path adjustments [66,67]. RRT is effective in rapidly navigating high-dimensional spaces; however, its dependence on random sampling frequently leads to suboptimal paths, requiring subsequent post-processing to enhance efficiency and smoothness [20]. D Lite* enhances efficiency in dynamic environments through incremental replanning; however, it is constrained in highly dynamic scenarios, where frequent changes may result in heightened computational delays and diminished path quality over time [38]. The inherent limitations highlight the need for the proposed SBPP, which aims to offer a more adaptive, efficient, and precise method for path planning in dynamic environments, thereby addressing the deficiencies of current algorithms. By considering reachability and time-limiting conditions, the system ensures stability and efficiency, which are crucial for sustainable supply chain operations. The dynamic allocation of tasks and real-time recalculations allow UAVs to adapt to changing conditions, ensuring that the supply chain network remains resilient and responsive. The routing policy algorithm is shown in Table 1.

3.7. Development of 3D path planning via SBPP

The SBPP method is an advanced version of the heuristic D* Lite algorithm designed specifically for a 3D environment. First, the environment, composed of a source and a destination, is divided into large blocks. Afterward, the blocks without obstacles are combined to form a large block. The D* Lite algorithm is then used to find a rough path between these blocks. Now, the blocks are further explored, and the shortest path in the blocks is determined. The process is repeated if an obstacle is introduced into the environment until the path is calculated.

3.7.1. Generation of sequential blocks

The SBPP method starts by creating abstract grids of cubic nodes, which the modified D* Lite algorithm uses as the map representation. Each node in these grids is represented by a coordinate tuple, (x,y,z). These grids are designed to simplify the search process by starting with the lowest resolution. Higher-level grids, such as Level 1, are more detailed, with each level becoming progressively coarser. The process begins by planning a preliminary abstract path, which is then refined through higher-resolution grids. Finally, the detailed paths between abstract grids are calculated via Level 1 nodes.

3.7.2. 3D Environment without obstacles

Sequential block generation in a 3D environment without obstacles is similar to 2D path planning. To plan the rough path, entrances are established between neighboring grids with adjacent level 1 nodes. The G_1 and G_2 grids share adjacent lines of nodes l_1 andl_2, with each line belonging to a different grid. Moreover, $n \in l_1 \cup l_2$, $symm(n)$in a node that is a symmetric node is located at l_2, which is positioned symmetrically relative to the border of the two grids. On the basis of this definition, an entrance e is a set of nodes that satisfy the following conditions:

a. An entrance e is confined to the limits of l_1 and l_2 and cannot exceed these boundaries.

a. l_1Nodes must have equivalent symmetric nodes in $l_2 \forall n \in l_1 \cup l_2 : n \in e \Leftrightarrow symm(n) \in e$
b. An entrance e must not include any obstructed nodes.
c. An entrance can extend in both directions up to the point where any of the other conditions would be violated.

SBPP outlines the transitions within each defined entrance, utilizing the modified D* Lite algorithm on these transition nodes to establish a rough path. For entrances exceeding a specified length, two transition points are placed at either end. This approach allows UAVs to efficiently navigate a three-dimensional space for logistics operations efficiently, ensuring optimal performance.

3.7.3. 3D environment with obstacles

Navigating a 3D environment with obstacles presents significant challenges. Unlike the continuous redefinition of entrances between grids, the modified D* Lite algorithm uses grid dimensions to identify successor nodes, eliminating the reliance on grid borders. Successor nodes are defined as the 26 nodes surrounding a given node nnn within a cubic arrangement at a distance matching the grid dimension. This allows for quick calculation of successor nodes and enables immediate replanning when the current path is invalid without the need for map corrections. Consequently, this approach requires less storage space since it does not necessitate maintaining lists of valid transition nodes and their successors. Instead, only the grid dimensions at each level are stored.

One issue with this method is that the start node might become a hierarchical successor. This is addressed by checking the distance between the start node and the node being expanded. Suppose the distance is within twice the grid size. In that case, the node is considered a successor, thereby eliminating the need for a final short transition and reducing the number of nodes that need to be expanded.

To handle obstacle avoidance in rough path calculations, Modified D* Lite employs Bresenham's Line Algorithm to verify the line-of-sight between nodes [61]. Nodes that lack lines of sight are not considered successors. This line-of-sight check is conducted only at the highest level of pathfinding, as visibility is already determined when refining paths at lower levels. Although this can increase computational costs due to greater distances between nodes at coarser levels, the line-of-sight checks are restricted to instances where at least one node falls within the UAV's search radius, thereby optimizing performance.

The modified D* Lite algorithm starts by setting up the node variables. All g values and rhs values are initialized to infinity, except for the goal node, which is set to $0 rhs(n_{dest})$. This makes the goal node the only inconsistent vertex n_{dest}, so it is added to the open set U. For large maps, initializing every node to infinity is inefficient and memory intensive, so nodes are instead initialized as they are encountered. The algorithm then calculates the shortest path from the start to the goal location, operating similarly to a reversed A* algorithm, ensuring completeness and optimality. If the rhs value of the start node is infinity, it signifies that no path exists between the start node and the goal $g(n_{start}) = \infty$. When a path is found, the UAV proceeds to the next node along the optimal path n_{start}. The environment is continuously monitored for changes, and if new obstacles are detected, the algorithm recalculates

Table 1
Queueing theory based sustainable supply chain routing policy.

1. Parameters are initialized as

i. Environment Ω with area $\boldsymbol{A}$, there are $M = \{1, 2, \ldots, M\}$UAVs with $T = \{1, 2, \ldots, T\}$tasks.
ii. $\bar{t} = \bar{t}_w + \bar{t}_s$, where $\bar{t}$is time between task arrival and completion, t_w is the waiting time of the task and $\bar{t}_s$is average time of logistic task distribution

2. If $T = 0$, UAVs fly on circular paths of radius $\mu = \{\mu_1, \mu_2, \ldots, \mu_M\}$about median of$\Omega$. The direction of flying is not specific, and it should be selected to reduce time when task is arrived
3. If $T \leq M$, the routing policy for each UAV on the basis of queueing theory is calculated.
4. Intertask distance matrix $\Gamma(t)$ is calculated using Eq. (31).
5. The state vector for each UAV is defined using Eq. (32).
6. The logistics task proximity cost vector is calculated for each UAV using Eq. (33).
7. The queueing vector is formed with each element representing a supply chain task for a UAV. The elements are defined as minima of a vector calculated for each UAV.
8. After tasks are allocated to each UAV, the logistics path to the destination is calculated using the SBPP method.
9. Repeat Steps 2–8

the rhs values for the affected nodes to maintain Eq. (25). The status of these nodes in the open set U is updated as needed, and the key values in U are refreshed to ensure that the queue is current. This re-evaluation process repeats, ensuring the consistency of each node until the UAV either reaches its target or no longer has a viable path. This approach allows the UAV to adapt dynamically to changes in the environment, maintaining effective navigation throughout its mission.

The UAVs must adhere to the routing policy to minimize travel distances and ensure the timely completion of tasks by avoiding collisions, as presented in Fig. 3. By considering reachability and time-limiting conditions, the system ensures stability and efficiency, which are crucial for sustainable supply chain operations. The dynamic allocation of tasks and real-time recalculations allow UAVs to adapt to changing conditions, ensuring that the supply chain network remains resilient and responsive. The detailed algorithm of the SBPP method is shown in Table 2.

4. Experiments and results

To verify the performance of the proposed 3D routing and path planning method for developing a more sustainable supply chain, we designed a series of experiments tested through a simulation process. A map with obstacles is created with the parameters listed in Table 3. Two simulation cases are discussed here. In the first case, 3D path planning of a single UAV using the proposed SBPP method is presented to demonstrate the modified D* Lite algorithm mechanism. In the second case, four destinations and four UAVs are selected randomly. Queueing theory is used to allocate destinations to UAVs, and then the SBPP method is used for path planning.

In the first case, a single UAV travels from the start node to the destination node. Figs. 4,5,7 and 7 represent path planning from Level 4 to Level 1, respectively. Furthermore, these figures illustrate that paths at different levels can vary widely depending on the path planning algorithm. In the level 4 plot, a rough path is proposed, and some sequential blocks include obstacles. However, blocks are gradually updated at Levels 3 and 2, and finally, a path is planned at Level 1. We can see that the generated path results in a sharp turn that may be difficult to execute.

The simulation results show that the proposed routing and path planning method results in a clear and sharp path despite obstacles. The results also demonstrate that the proposed method only operates at 4 levels, thus providing efficiency in terms of computational cost, which is crucial for developing a sustainable supply chain.

In the second case, four UAVs and four tasks were selected randomly in the simulation environment described in Table 3. Queueing theory was used to determine specific tasks for each UAV. Table 4 shows the obtained optimal proximity cost values with the corresponding UAVs and target destinations.

After destination locations are allocated to particular UAVs, the SBPP method determines the optimal path for each UAV. The path planning for all the UAVs is shown in Figs. 8,9,10, and 11. The figures show the top views of the generated paths. The simulation results clearly show that the proposed routing and path planning method results in clear and sharp paths even in the presence of obstacles, supporting the development of a sustainable supply chain by ensuring efficient and reliable UAV operations.

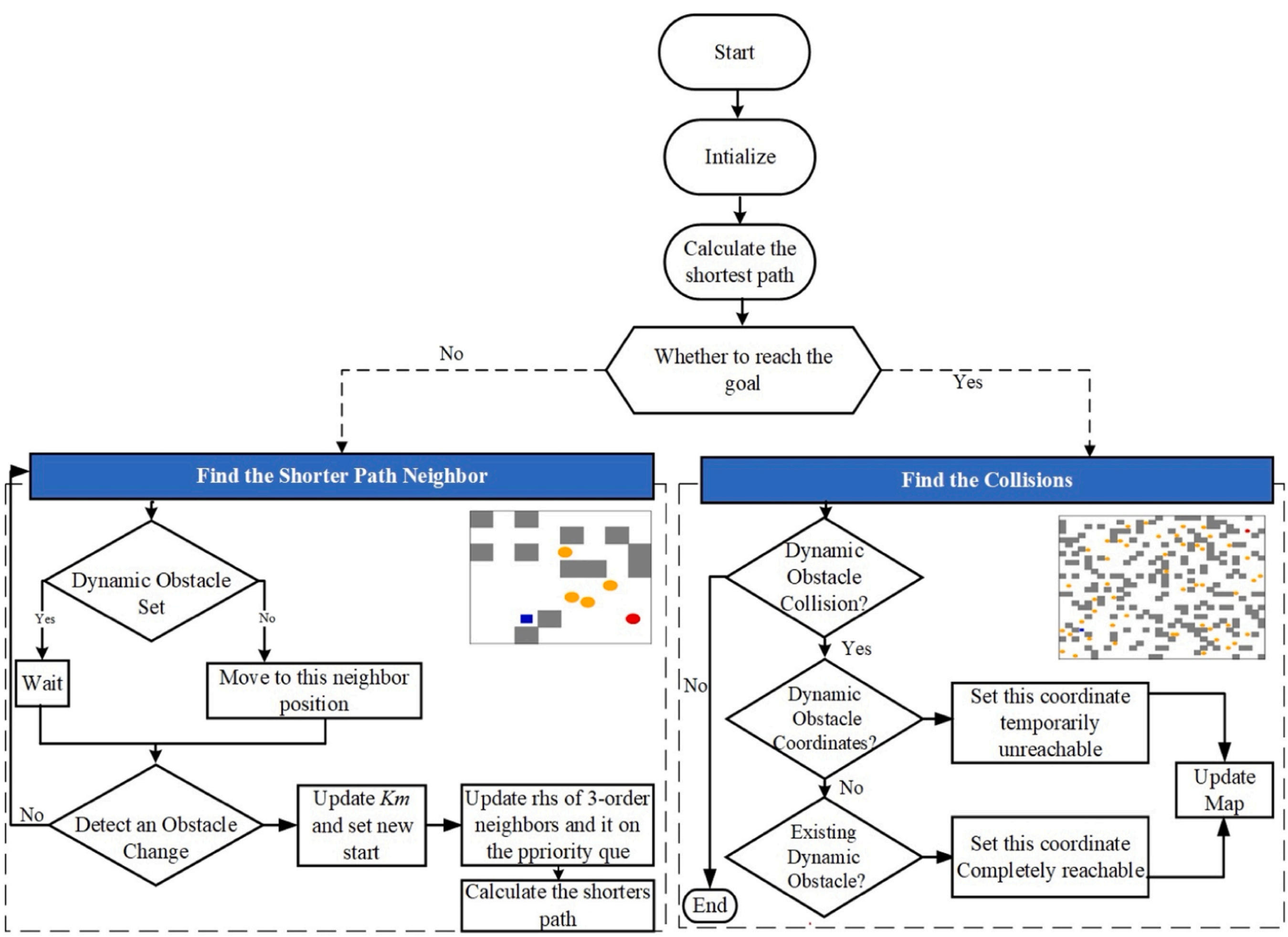

Fig. 3. *:* SBPP method with modified D* lite algorithm flowchart.

Table 2
SBPP method with modified D* lite algorithm for sustainable supply chain routing.

1. All parameters are initialized as
$U = \varnothing$
$rhs(n) = g(n) = \infty$ for all $n \in S$
$rhs(n_{dest}) = 0$
$U.Insert(n_{dest}, CalcKey(n_{dest}))$
U.Pop() function deletes and retrieves the node with the lowest priority value
U.TopKey() function represents the key values associated with the node that is returned by U.Pop().
2. Call Routine "Calculate_Shortest_Path"
3. Follow Step 4-Step 6, until $n_{start} \neq n_{dest}$ else End
4. If $g(n_{start}) = \infty$ then no path exist and Algorithm is End
5. Calculate $n_{start} = \text{argmin}_{n' \in succ(n_{start})}(g(n') + J(n_{start}, n'))$ and move to n_{start}
6. Scan new obstacles in the environment, if new obstacles exist then follow Step 7–9 else Go to Step 3.
7. Update Cost function $J(u, v)$ and Call Routine "Update_Vertex(u) for all edges
8. For all nodes $n \in S$, U.Update($n, CalcKey(n)$)
9. Call Routine "Calculate_Shortest_Path"

***Routine** CalcKey(n)*
$\min(g(n), rhs(n)) + h(n, n_{start}))$; $\min(g(n), rhs(n))$
***Routine** Update_Vertex(u)*
if $u \neq n_{dest}$ then $rhs(u) = \min_{n' \in succ(u)}(J(u, n') + g(n'))$
if $u \in U$ then U.remove(u)
if $g(u) \neq rhs(u)$ then U.Insert($u, CalcKey(u)$)
***Routine** Calculate_Shortest_Path*
Repeat following until U.TopKey() $< CalcKey(n_{start})$ or $rhs(n_{start}) \neq g(n_{start})$
$u =$ U.pop()
If $g(u) > rhs(u)$ then $g(u) = rhs(u)$ and Call Routine *Update_Vertex(n)* for all $n \in succ(u)$
else $g(u) = \infty$ and Call Routine *Update_Vertex(n)* for all $n \in succ(u) \cup \{u\}$

Table 3
Simulation parameters.

No.	Parameter	Value
1	Map Size	64 × 64 X 64
2	Obstacle volume	12 %
3	Heuristic	1.00
4	Path finding Time Limit	Nil

The performance of the proposed SBPP method is also compared with that of the standard A* and D* algorithms, as shown in Table 5. The comparison clearly shows that, compared with the other methods, the proposed method results in an optimal path concerning a reduced pathfinding time. Notably, improved performance is also attained with routing based on queuing theory. Hence, the proposed method has improved and computationally cost-effective 3D routing and path planning for a group of UAVs, which is a significant factor in developing a sustainable supply chain. Table 5 demonstrates that SBPP surpasses both A* and D* Lite in execution time and exhibits superior obstacle-handling capabilities. In contrast to A* , which recalculates the entire path upon encountering obstacles, and D* Lite, which updates paths incrementally but may experience inefficiencies with frequent changes, SBPP effectively divides the environment into sequential blocks. This segmentation facilitates localized modifications without the need to recalculate the entire path, thereby ensuring smoother transitions around obstacles and minimizing computational overhead.

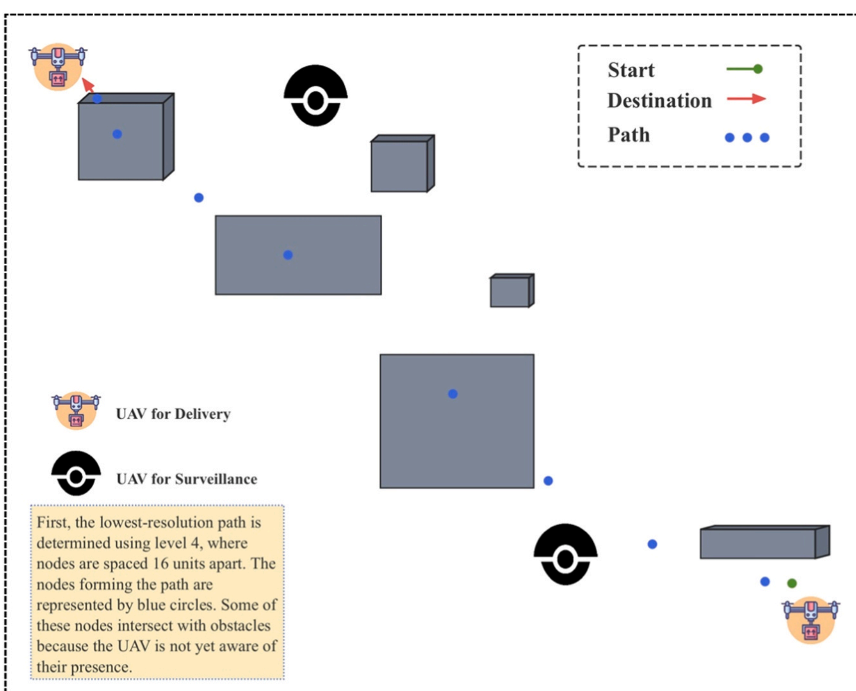

Fig. 4. *:* Step 1, level 4 map.

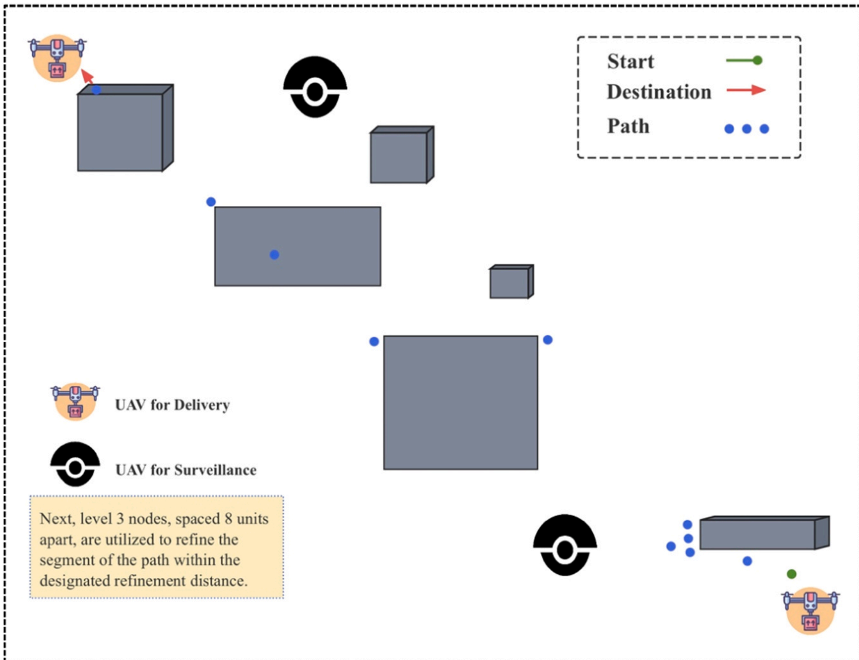

Fig. 5. *:* Step 2, level 3 map.

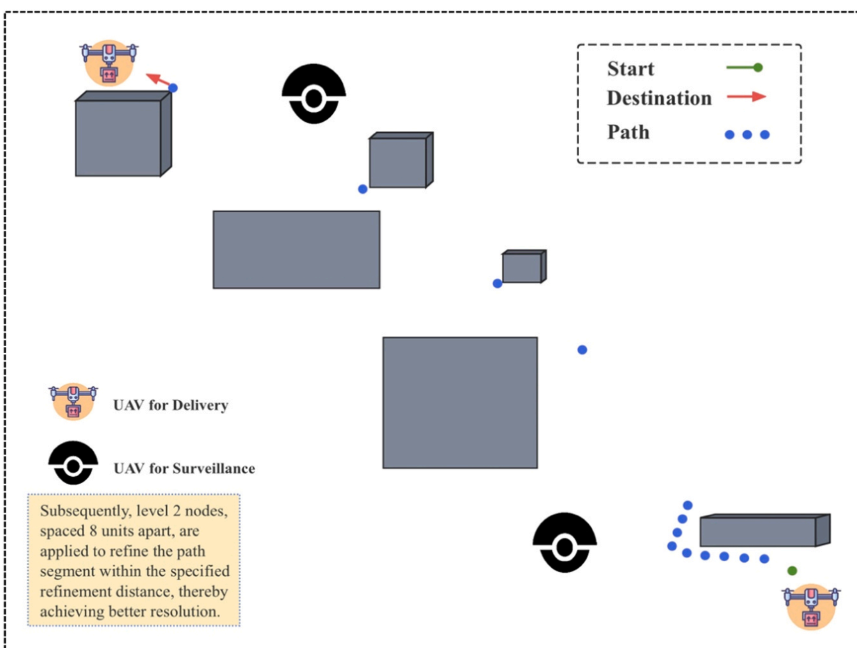

Fig. 6. *:* Step 3, level 2 map.

Furthermore, the adaptive characteristics of SBPP in managing dynamic obstacles enhance its performance in complex environments.

The performance of the proposed SBPP method is also compared with that of the standard A* and D* algorithms. The results shown in case 2 are repeated with the standard A* and D* algorithms, and paths planned by the three methods are shown in Fig. 12 (a, b, c, and d). The cyan color shows the path generated by the SBPP method; the red color shows the path generated by the D* algorithm; and the blue color shows the path generated by the A* algorithm. Fig. 10 clearly shows that the shortest path is planned via the SBPP method. It is also clear that the path generated via the SBPP method is relatively smooth compared with those generated via the other methods. In addition, the obstacle handling ability of SBPP is better than that of other methods, which can be observed via visual inspection of these results.

The proposed 3D routing and path planning method carries significant practical implications, particularly in the realm of sustainable supply chain management. By optimizing UAV routes in three-dimensional spaces, this method not only enhances the efficiency of logistics operations but also reduces both energy consumption and operational costs. The integration of queuing theory for task allocation ensures a balanced workload among UAVs, thereby preventing bottlenecks and ensuring timely delivery of goods. Previous studies have shown that efficient routing algorithms for UAVs can significantly reduce energy consumption, thereby contributing to sustainability goals

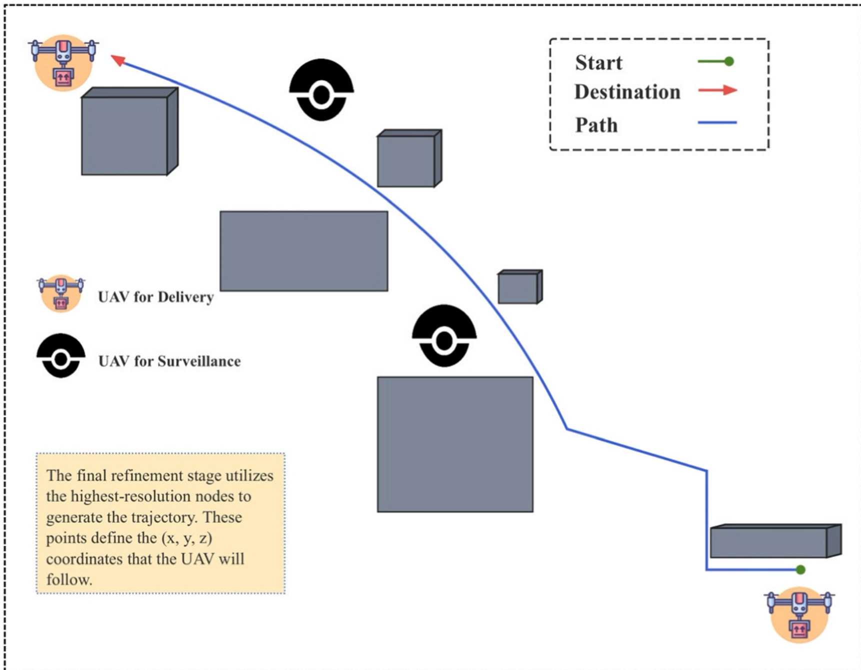

Fig. 7. : Step 4, Level 1 map for more sustainable supply chain routing.

Table 4
Queueing based UAV sustainable supply chain routing.

No.	UAV Coordinates	Target Coordinates	Proximity Cost
1	(2,1,3)	(40,40,10)	93.16
2	(3,3,6)	(60,55,12)	170.14
3	(4,2,6)	(60,62,6)	279.74
4	(6,6,12)	(50,1,6)	314.51

[14,44]. The SBPP method, by minimizing travel distances and avoiding obstacles, ensures that UAVs consume less energy, extend their operational time, and reduce the frequency of battery recharges or replacements. Efficient path planning also reduces UAV wear and tear, thereby lowering maintenance costs. Moreover, by optimizing task allocation and route planning, the method reduces the overall number of UAVs required to perform a set of tasks, leading to cost savings in fleet management [18]. The method's adaptability to dynamic environments ensures high reliability and responsiveness of the supply chain, a crucial feature for real-world applications where environmental conditions and task requirements can change rapidly [70].

The proposed method also offers several theoretical advancements in the field of UAV routing and path planning. It builds on existing algorithms and introduces novel modifications that enhance performance in three-dimensional spaces, thereby contributing to the broader body of

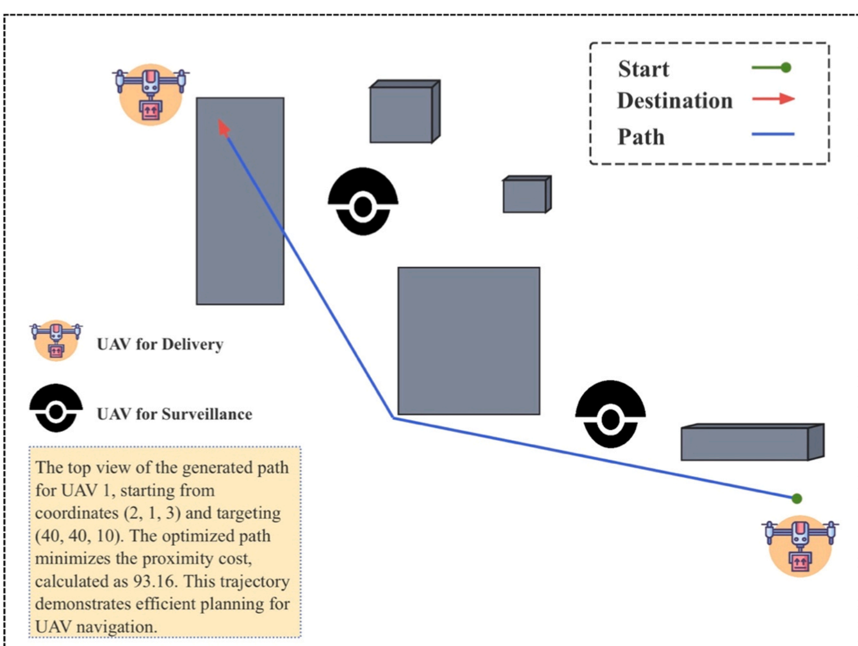

Fig. 8. : Top view of the generated path for UAV1.

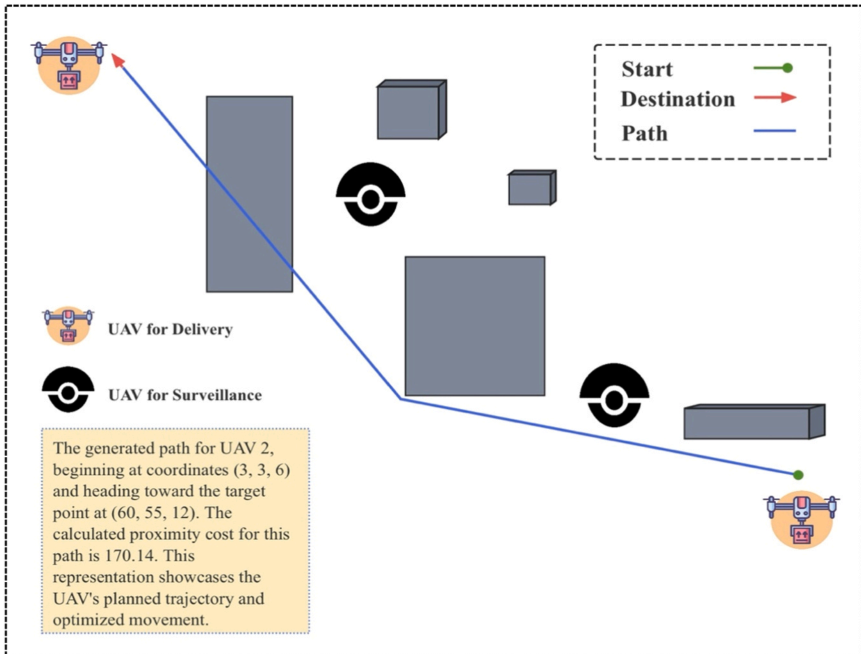

Fig. 9. : Top view of the generated path for UAV2.

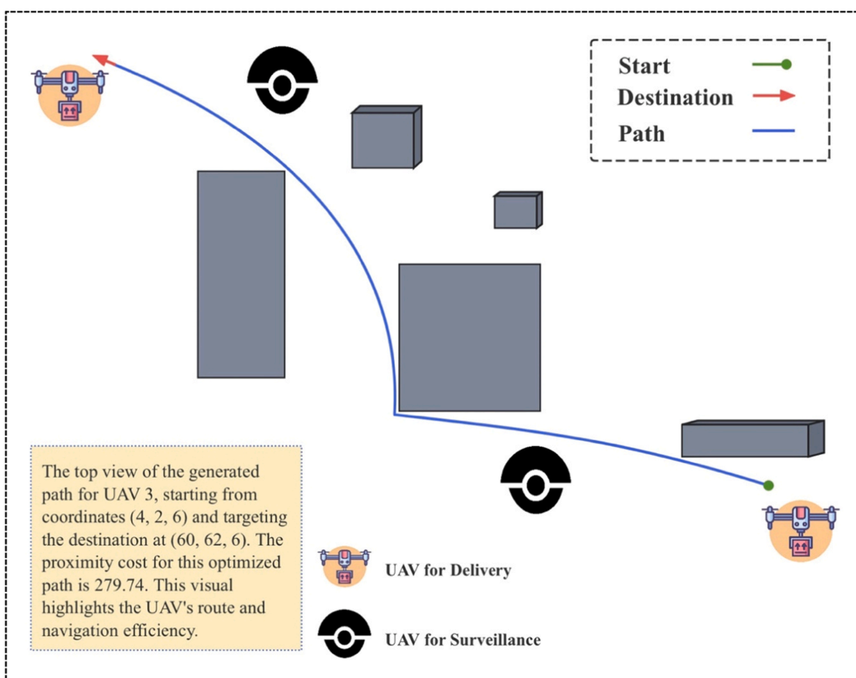

Fig. 10. : Top view of the generated path for UAV3.

knowledge in this area. The modifications to the D* Lite algorithm, which is specifically designed for 3D environments, provide a new approach for handling the complexity of three-dimensional pathfinding. This contributes to the theoretical understanding of how heuristic algorithms can be adapted for more complex spatial environments. The proposed method bridges a gap between routing optimization and task scheduling by integrating queuing theory into the task allocation process. This interdisciplinary approach enhances the theoretical framework for UAV operations, providing a holistic view of how different optimization techniques can work together [1]. The method's ability to operate efficiently even in large-scale environments demonstrates its scalability. Theoretical models of computational complexity and efficiency are supported by the practical results of the simulations, providing a robust validation of the proposed approach [37]

In this study, the simulation results show that the proposed routing and path planning method results in clear and sharp paths even in the presence of obstacles, supporting the development of a sustainable supply chain by ensuring efficient and reliable UAV operations. By combining advanced pathfinding algorithms with queuing theory, the method offers both practical benefits and theoretical advancements, making it a significant contribution to the UAV logistics and supply chain management field.

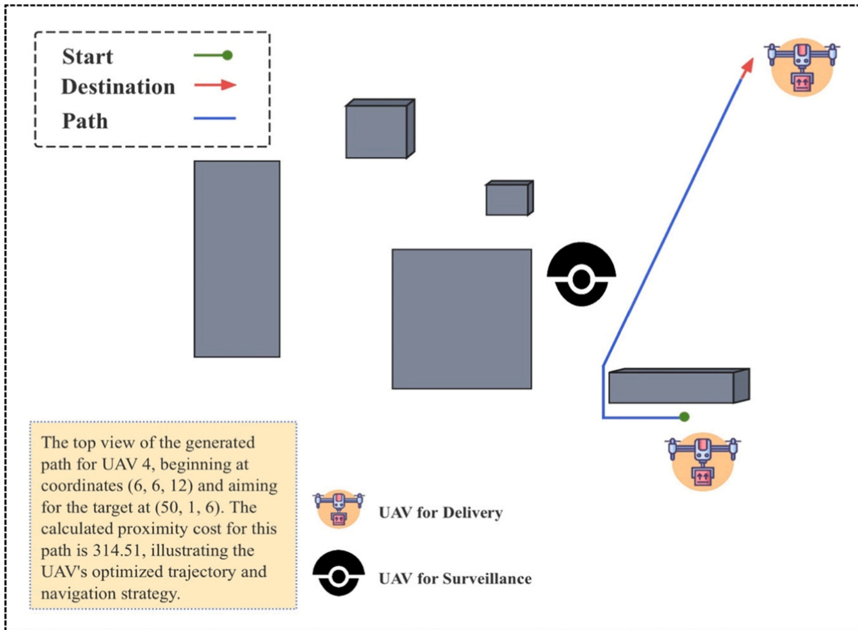

Fig. 11. : Top view of the generated path for UAV4.

Table 5
Comparison of SBPP with other path planning algorithms for sustainable supply chain routing.

No.	UAV Coordinates	Target Coordinates	A* Path finding time (ms)	D* Path finding time (ms)	SBPP Path finding time (ms)
1	(2,1,3)	(40,40,10)	42.43	40.75	34.35
2	(3,3,6)	(60,55,12)	36.82	35.74	30.72
3	(4,2,6)	(60,62,6)	24.37	22.84	18.06
4	(6,6,12)	(50,1,6)	45.36	44.64	40.21

To develop three-dimensional unmanned aerial vehicle (UAV) supply chain routing that enhances the sustainability of supply chain management, practitioners and researchers can integrate path planning and queuing theory. Path planning ensures efficient and optimal routes for UAVs, minimizes energy consumption, and reduces the carbon footprint associated with logistics. By leveraging advanced algorithms, UAVs can navigate complex environments and deliver goods with precision, reducing the need for traditional, less efficient transportation methods. Queuing theory, on the other hand, helps manage the flow and scheduling of UAVs, ensures timely deliveries, and reduces wait times. This systematic approach not only improves the overall efficiency of the supply chain but also contributes to strategic sustainable supply chains [57] by minimizing resource waste and optimizing operational performance. Combining these methodologies enables a robust framework for UAV supply chain routing, aligning technological advancements with sustainable business practices.

5. Conclusion

Researchers in this study aimed to propose an improved and efficient path planning algorithm for UAV networks in uncertain, dynamic 3D environments coupled with optimized UAV routing for sustainable supply chain management. The primary objective was to increase the efficiency and sustainability of UAV logistics operations by introducing novel methodologies. A key contribution of this research is the introduction of the SBPP method, a modified version of the heuristic D* Lite algorithm, which provides the shortest logistics path with reduced computation time compared with contemporary methods. Additionally, queuing theory was employed for task scheduling and the assignment of UAVs within the supply chain network, ensuring effective and efficient task distribution.

The simulation results demonstrated that combining the proposed routing and path planning algorithms significantly improved performance in 3D environments, delivering shorter logistics paths without collision issues within supply chain routing. The computation time was also notably reduced compared with that of other techniques used in similar 3D environments. This indicates substantial advancements in UAV network management, particularly in terms of efficiency and operational effectiveness.

The results of this study have practical implications for UAVs in logistics management, especially in the context of sustainable supply chains. By developing an efficient sequential block path planning method and enhancing task distribution through queuing theory, this research provides a framework that can directly support real-world UAV logistics operations. Specifically, the proposed method reduces computation time and optimizes flight paths, allowing UAVs to execute quicker, more accurate deliveries while minimizing environmental impacts. This approach aligns with sustainability goals by cutting unnecessary fuel usage, lowering emissions, and streamlining operations in complex 3D environments—attributes critical for logistics managers seeking to balance operational efficiency with environmental responsibility. The methodologies introduced here offer UAV fleet operators a powerful tool for optimizing resource allocation and routing decisions, potentially transforming supply chain logistics by enabling faster, safer, and more sustainable aerial transport across industries.

Furthermore, this study contributes significantly to the development a novel sequential block path planning method for 3D unmanned aerial vehicle Routing in sustainable supply chains. By integrating path planning, SBPP, and queuing theory, this research offers a holistic approach to managing UAV operations in supply chains. This integration ensures efficient and sustainable routing that minimizes environmental impact while maximizing operational efficiency. The findings highlight the potential for these methodologies to be applied broadly in various supply chain contexts, paving the way for more sustainable and efficient logistics solutions.

Despite these promising results, this study has limitations. First, the proposed algorithms were tested in simulated environments, which may not fully capture the complexities and unpredictability of real-world

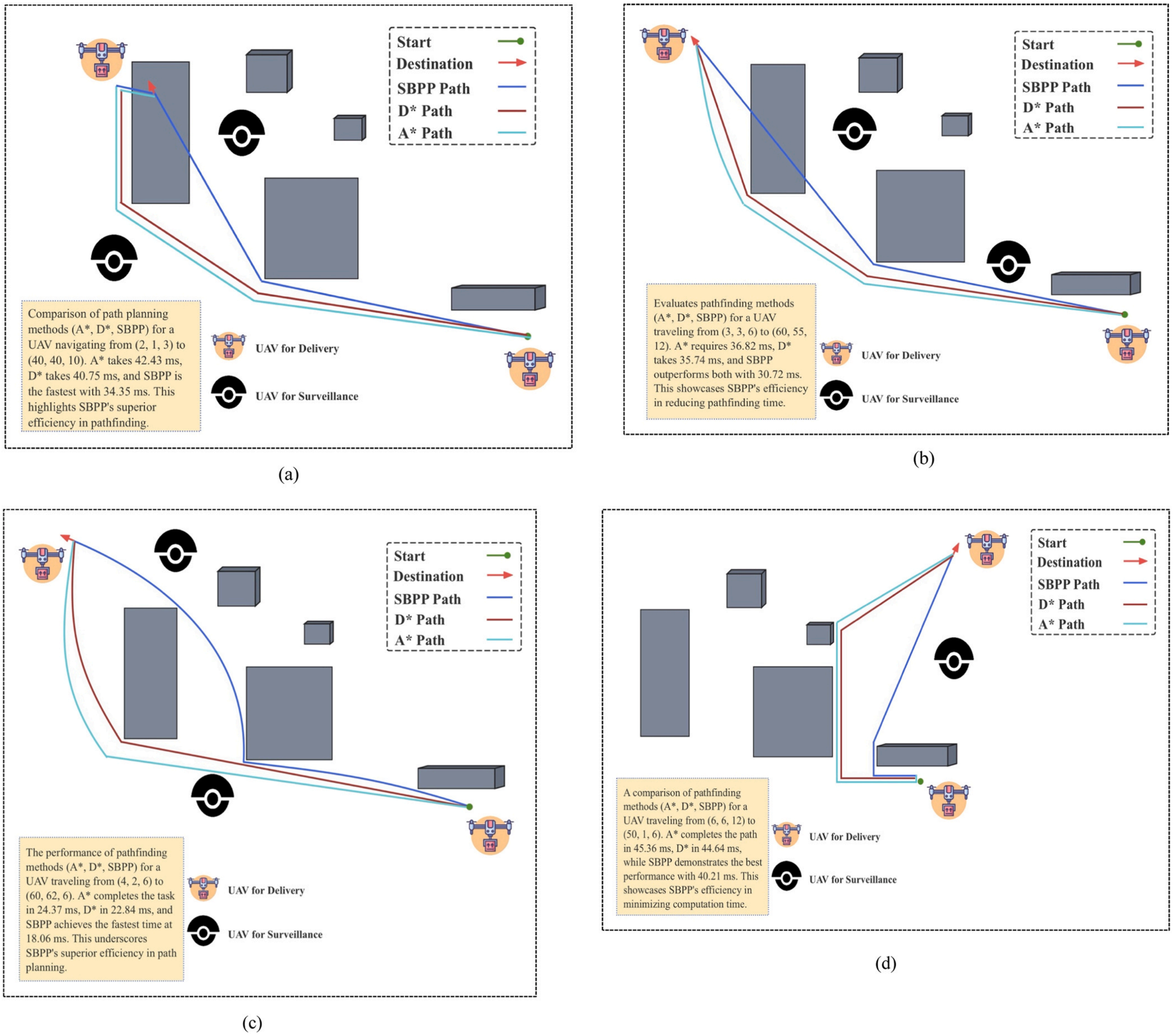

Fig. 12. *(a, b, c, d):* Comparison of path planning methods (SBPP, D*, A*).

scenarios. Second, the model does not account for potential hardware limitations or failures of UAVs, which could impact the effectiveness of the proposed algorithms. Third, the study focuses on a specific type of dynamic environment, and the generalizability of the findings to different or more complex environments remains to be explored. Finally, the integration of queuing theory, while beneficial for task scheduling, may not fully address all real-time dynamic changes in UAV networks.

Future research should address these limitations by testing the proposed algorithms in real-world environments to validate their effectiveness and robustness. Additionally, incorporating more advanced and adaptive elements into the model to handle unexpected UAV failures or hardware limitations would enhance the reliability of the system. Further studies could explore the application of these algorithms to a wider range of dynamic environments to assess their versatility and scalability. Finally, integrating machine learning techniques could improve the adaptability and efficiency of UAV routing and path planning in real-time, dynamic situations, providing more comprehensive solutions for sustainable supply chain management. Future research should also continue to develop and refine 3D UAV sustainable supply chain routing, focusing on minimizing environmental impact while ensuring efficient and effective logistics operations.

CRediT authorship contribution statement

Prof. Robert Sroufe: Writing – review & editing, Validation, Investigation, Conceptualization. **Muhammad Ikram:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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.

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