Role of Unmanned Air Vehicles (UAVs) in Sustainable Supply Chain: Queuing Theory and Ant Colony Optimization Approach

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Abstract

The COVID-19 pandemic disrupted global supply chains and posed significant challenges to human lives. Innovative strategies, such as employing robotics and autonomous systems (RAS), including Unmanned Air Vehicles (UAVs), can mitigate these challenges. Although UAVs are increasingly used in various commercial applications, nonetheless, it is imperative to strategize path planning effectively to address supply chain operations, and circumvent collisions and congestions. This study aims to develop a 3D path planning algorithm for UAVs using the Ant Colony Optimization (ACO) metaheuristic algorithm, considering the convenience of applying queuing theory in a three-dimensional space. The generated paths will be compared to previous works that used conventional methods. Furthermore, we will use the Interfered Fluid Dynamical Systems (IFDS) and Lyapunov Guidance Vector Field (LGVF) hybrid algorithm, which has shown superior performance compared to ACO in terms of computational time and multiple path creation. Additionally, this study develops a framework to avoid supply chain obstacles and possible collisions with multiple UAVs. Despite the increased use of drones in supply chains, there is a gap

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between academic research and industry adoption. This study aims to bridge this gap by providing insights for more sustainable supply chain operations using UAVs.

Keywords: UAVs; Sustainable; Supply Chain; autonomous systems; Queuing theory; Colony Optimization; Security & privacy

1. Introduction

The supply chain sector is a vital component of contemporary business activities, encompassing the administration of products and services from their genesis to the final consumer. This intricate process engages various stakeholders, such as manufacturers, suppliers, distributors, retailers, and end-users. Effectively managing the supply chain is imperative for business success, as it influences aspects like client contentment, cost-effectiveness, and environmental sustainability (Parajuli et al., 2019).

A recent publication from MarketsandMarkets has projected an increase in the UAV logistics and transportation market from USD 11.20 Billion in 2022 to USD 29.06 Billion by 2027, with a compound annual growth rate (CAGR) of 21.01% (MarketsandMarkets, 2020). Concurrently, an independent report by DRONEII has also forecasted a rise in the global UAV market from USD 14 Billion in 2018 to above USD 43 Billion in 2024, marking a CAGR of 20.5% (DRONEII, 2019). Industry leaders like Amazon, DHL, Federal Express, Google, and Facebook are actively investigating the applicability of drone technology in logistics, package delivery, and internet connection transmission (Lee and Choi, 2016; Wang, Poikonen, and Golden, 2017). The envisioned role of drones in these companies' business models primarily revolves around last-mile delivery and direct transportation of packages from the depot to the end-users (Es Yurek and Ozmutlu, 2018).

In the contemporary business landscape, sustainable supply chain management has emerged as a significant concept. This approach entails the fusion of environmental, social, and economic considerations within the supply chain operations. Its primary objective is to protect the environment while also ensuring economic sustainability (Sarkis, 2020). By adopting sustainable supply chain practices, businesses can bolster their reputation, decrease expenses, and elevate stakeholder value.

A major challenge confronting the supply chain sector is the transportation of goods. As a vital component of the supply chain process, transportation accounts for a considerable portion of the overall costs. Conventional transportation methods, such as trucks and ships, are often slow and emit large amounts of carbon dioxide. Unmanned Air Vehicles (UAVs), or drones, have emerged as an innovative solution to this issue.

A UAV is a remotely piloted aircraft that does not require a human operator onboard. They have been utilized in diverse applications, such as military surveillance, photography, and video production. The adoption of UAVs within the supply chain industry has accelerated in recent years due to their ability to increase delivery speeds, decrease transportation expenses, and diminish carbon footprints (Triche et al., 2020). Capable of navigating traffic and bypassing congestion, UAVs facilitate expedited deliveries (Chiang et al., 2019). Additionally, UAV's can be deployed quickly and do not require extensive infrastructure, such as airports or ports, making them a cost-effective transportation option. Moreover, UAVs can reduce CO_2 substantially, enhancing supply chain sustainability (Chiang et al., 2019).

While UAVs hold immense promise for the supply chain sector, their incorporation is not without hurdles. A primary challenge lies in the regulatory framework governing their use. Aviation authorities worldwide enforce varying regulations, which can impede seamless integration (Sun et al., 2019). Additionally, privacy and security concerns related to UAV deployment must be addressed. To implement UAVs in the supply chain, these challenges need to be examined and navigated thoroughly. By carefully considering regulatory constraints and addressing privacy and security issues, businesses can harness the potential of UAVs to transform their supply chain operations.

Costs associated with supply chain and logistics encompass transportation, warehousing, and order processing expenses. Companies can diminish these by integrating UAV'sinto their supply chain management (SCM) and logistics procedures. From a cost perspective, UAV'sare potentially more economical and environmentally friendly compared to trucks, given they are battery-operated instead of relying on gasoline (Ha et al., 2018). The incorporation of UAV'sin delivery operations is expedient and cost-effective in terms of per kilometre transportation expense (Wang et al., 2019). Shavarani et al. (2019) predict that aerial delivery systems could lead to annual cost savings upwards of USD 50 Million. Drones, in contrast to traditional delivery vehicles like trucks, incur lower maintenance costs and have the potential to decrease labour expenses by performing tasks independently (Dorling et al., 2017). Moshref-Javadi, Lee, and Winkenbach (2020) propose that drones, when combined with trucks, can lead to significant cost savings, especially for deliveries in suburban regions with moderate density. UAV'sfacilitate prompt delivery of products to customers, thereby supporting efficient SCM and logistics operations and circumventing delay-related costs.

The maneuverability of air defense weapons has consistently been a focal point in ongoing research concerning unmanned aerial vehicles (UAVs) path planning (Qadir et al., 2021). As defined by Vagale et al. (2021), path planning for autonomous vehicles involves devising an optimal route from the starting point to the destination while circumventing obstacles. The authors further emphasize that path planning has been instrumental in enhancing the level of autonomy for UAVs.

A path planning technology must meet four fundamental requirements: high computation efficiency, safety, optimization, and feasibility (Puente-Castro et al., 2022). UAV performance and autonomy can be improved through innovations in path planning (Wan et al., 2022).

The purpose of this chapter is to discuss the challenges of collision avoidance in supply chain scenarios involving multiple UAV deployments at a predetermined arrival rate. This paper explores three-dimensional (3D) path planning for UAVs by utilizing queuing theory, in which space is divided into three sections between two points-A and B. The UAVs deployed in the supply chain system must have an exponentially distributed arrival rate and navigate from point A to point B, with the arrival information updated periodically over a fixed time interval.

This chapter aims to develop and implement a path planning algorithm for UAVs that allows new UAVs to alter their routes when they encounter potential collisions. The UAVs' speed must also be adjustable to avoid congestion in situations where one UAV is ahead of the others. By effectively addressing these challenges, the paper aims to improve the safe and efficient integration of UAVs into supply chain systems.

A UAV's integration into supply chain management can open up new opportunities for businesses. For instance, this technology can facilitate same-day delivery services, resulting in enhanced customer satisfaction and increased revenue, even in cases involving multiple UAV collisions. Moreover, UAVs enable businesses to expand their reach into remote areas, helping them gain a greater share of the market (Colajanni et al., 2022).

There are a variety of strategies that can be used to optimize the integration of UAVs into the supply chain. Queueing theory offers a mathematical framework for analyzing and optimizing waiting lines, among other things. The application of queueing theory can help pinpoint supply chain bottlenecks and optimize the flow of goods. ACO uses a metaheuristic algorithm based on ant behavior to solve optimization problems, which has proven effective. ACO can enhance efficiency and reduce costs by optimizing UAV routing and scheduling. These approaches can allow businesses to fully leverage the potential of UAVs in supply chain management.

The integration of UAV technology, queueing theory, and ACO results in greater efficiency and sustainability of supply chain processes. In addition to producing new opportunities for businesses, UAV integration in the supply chain can also enable same-day delivery services, leading to higher customer satisfaction and higher revenue.

This chapter explores the role of UAVs in sustainable supply chains and applies queueing theory and ACO to supply chain process optimization. Furthermore, this chapter will discuss potential research avenues for UAV integration into supply chains as well as challenges and opportunities associated with this process. This chapter contributes to the existing literature on sustainable supply chain management by providing valuable insights into operating multiple UAVs within a supply chain system.

This chapter is organized as follows. Section 2 delivers a review of contemporary literature on the application of UAVs in SCM, emphasizing the use of various algorithms. Section 3 provides an overview of different advanced methods achieved by integrating UAVs with SCM. In Section 4, results are demonstrated through a novel approach that tackles the issue of collision avoidance when deploying multiple UAVs. The final section of this chapter concludes the discussion, detailing the limitations and outlining potential future directions.

2. Literature Review

UAVs have captivated the interest of researchers and practitioners alike in recent years. This section examines various approaches employed to optimize the integration of UAVs into supply chains and the role of UAVs in supply chain management.

Numerous studies have investigated UAVs' potential for supply chain management from a transportation perspective. For example, Wang et al. (2021) put forth a drone-enabled transportation system for last-mile delivery. The authors devised a model to optimize the delivery process and demonstrated that drone usage could significantly decrease delivery time and costs. In a similar vein, Zheng et al. (2018) suggested a multi-UAV cooperative transportation system that could enhance the efficiency of last-mile delivery. Through simulation experiments, the authors illustrated that this system could markedly reduce delivery time and boost UAV utilization rates. Additionally, UAVs have been used in the supply chain for inventory management. Kurniawan et al., (2019) suggested an inventory management system employing UAVs for stock-taking and inventory monitoring. The authors created a model to optimize inventory levels and demonstrated that UAV usage could reduce inventory holding costs and enhance inventory accuracy.

UAVs have also been used to monitor and inspect supply chains in addition to transportation and inventory management. For instance, Lee et al. (2019) introduced a UAV-based monitoring system for container yards. By using UAVs to monitor the container yard layout, the authors demonstrated that monitoring time could be significantly reduced and container yard safety could be improved significantly.

The optimization of UAV integration has been achieved through a variety of approaches, including optimization algorithms and simulation experiments. For example, Anagnostopoulos et al. (2023) presented an optimization model for integrating UAVs into supply chains. In the study, a genetic algorithm was used to optimize UAV routing and it was found that the model could significantly lower transportation costs and carbon emissions.

A similar approach is employed to optimize the integration of UAVs into supply chain management using queueing theory. Queuing theory offers a mathematical framework for analyzing and optimizing waiting lines. Zhou et al. (2021) proposed a queuing model for the optimal integration of UAVs in the supply chain. The authors demonstrated that utilizing queuing theory could help pinpoint bottlenecks in the supply chain process and optimize the flow of goods.

An optimization algorithm called Ant Colony Optimization (ACO) optimizes UAV integration in supply chain management. ACO is a metaheuristic algorithm based on ant behavior that has been successfully used to address optimization problems. Zhou et al. (2021) suggested an ACO-based algorithm for optimizing UAV routing in the supply chain. As a result of the algorithm, the authors showed that the supply chain was more efficient and transportation times were reduced.

A pioneering study on UAVs in logistics was conducted by (She & Ouyang, 2021). The study examined the feasibility of utilizing UAVs for last-mile delivery, concluding that UAVs could decrease delivery times and costs. In addition, She and Ouyang, (2021) conducted a study on using UAVs in the pharmaceutical supply chain, observing that they could improve efficiency and reliability.

The application of UAVs in disaster relief operations has also been studied in a number of studies. According to Kamat et al. (2022), UAVs could provide timely and effective assistance during disaster relief operations when used in humanitarian logistics. Similarly, Amiri et al. (2018) explored the application of UAVs in disaster response operations, concluding that UAVs could significantly increase the speed and efficiency of such responses.Yan et al. (2017) suggested a multi-objective optimization model for UAV-based logistics, which was shown to optimize transportation costs and delivery times.

UAVs are excellent at transporting goods rapidly, which is one of their primary benefits in supply chain management. In a study conducted by Maciel-Pearson et al. (2019), UAVs reduced parcel delivery times by up to 80%. Moreover, UAVs can deliver goods to remote areas where traditional transportation methods, such as trucks and ships, are not feasible. Additionally, UAVs can lower transportation costs by removing the need for airports and ports.

UAVs can significantly contribute to supply chain sustainability by reducing CO_2emissions. Goodchild and Toy, (2018) revealed that utilizing UAVs reduced CO_2 emissions by up to 95% compared to traditional delivery methods. The diminished carbon footprint can also result in improved corporate social responsibility (CSR) for businesses.

There are a number of challenges associated with UAV use in supply chain management, and one of them is the regulatory framework. The use of UAVs is regulated by aviation authorities, and these regulations differ across countries. For instance, in the USA, the Federal Aviation Administration (FAA) enforces strict regulations for using UAVs for commercial purposes. These regulations mandate businesses to obtain a remote pilot certificate and restrict the altitude and distance of UAVs. In contrast, regulations in countries such as China and Japan are less restrictive, leading to faster adoption of UAVs in the supply chain process (Kim, 2019).

Path planning for UAVs constitutes a significant portion of the literature reviewed. There is an extensive use of algorithms as a significant part of UAV research involves route optimization. Nevertheless, the need for further advancement and breakthroughs in UAV path planning remains. The prospects in this field are outlined as follows.

In industrial settings, UAVs typically fly below 400 m in low-altitude conditions. This complex environment presents unique challenges for UAV navigation algorithms. Thus, it's crucial for these algorithms to account for varying conditions such as altitude, wind speed, temperature, and humidity, adapting to the specific flight environment.

There's a scarcity of research focused on UAV navigation in urban contexts. Potential areas for exploration include improving the detail in flight environment modeling, increasing the efficiency of navigation algorithms, and enhancing the coordinated operations between UAVs and delivery vehicles. There's also scope to merge various algorithms to boost the algorithm's real-time decision-making efficiency. Currently, most navigation strategies target individual UAVs. With the trend moving towards UAV groups and smarter tech, future studies might explore advanced navigation techniques for UAV groupings.

There have been numerous algorithms and methods developed for path planning of UAVs by various authors, including Wahab et al. (2020). Furthermore, potential fields, cell decompositions, and potential fields are some of the general path planning techniques. It is important to consider both static and dynamic constraints in comprehensive path planning to avoid UAV collisions with adversaries. In this regard, dynamic obstacles present more dimensions in path planning for UAV navigation in space. While path planning for static obstacles involves space configuration, dynamic obstacles introduce an additional dimension to the space configuration: time. However, Dobrokhodov et al. (2020) suggested that incorporating the time dimension in the state space of UAV is more akin to trajectory or motion planning rather than path planning.

In a pivotal study within the realm of supply chain management logistics, Ben Amarat and Zong, (2019) explored the complexities of routing optimization for a singular vehicular entity traversing diverse potential trajectories. The methodology underscores the incorporation of a penalty weight to the anterior route chosen by a UAV during its successive planning stages. Within a spatial framework delineated by grid structures, grid cells charted by a specific UAV are accorded elevated penalty metrics, thereby signaling auxiliary UAVs to pursue alternate navigation strategies. The algorithmic schema, in its deployment, commences with a probabilistic map-based route formulation for the primary vehicle. This is succeeded by generating a modified spatial representation, superimposing penalty metrics on grid cells affiliated with the route of the principal vehicle. In the subsequent phase, drawing from this augmented spatial schematic, a trajectory is devised for the ensuing UAV. It's worth noting that this iterative methodology is scalable, adaptable for scenarios encompassing an array of UAVs within the supply chain logistics.

It is evident from the existing literature that UAVs have significant potential with respect to supply chain management. Supply chain processes can be made more efficient, faster, and sustainable by using UAVs. The integration of UAVs in supply chain management, however, faces several challenges, including regulatory and security concerns. To the best of the author's knowledge, this study is the first of its kind to highlight the issue of UAV collisions within the supply chain network. As a result, this study fills a gap in the literature by developing a multidimensional model for making the supply chain network more efficient and avoiding collisions with UAVs.

3. Methodology

This study aims to determine the most efficient path between points A and B without colliding by deploying multiple UAVs in the spatial system. The UAVs are required to have an exponential distribution arrival rate, and congestion is not desired in a given cell, as that may lead to collision. The proposed technique for the solution of the path planning is ACO.

This study uses mobile UAVs as artificial ants. A UAV inspired by real ants has been developed. Real ants move based on a chemical trail known as pheromone. The ants prefer the regions with the greatest concentration of this chemical trail among the available paths (Sharma et al., 2022). Pheromone, as discussed above, is left behind by the moving ants that guide the followers. In this case, the insects would tend to follow the rich area of the chemical trail, as described above. In this case, the pheromone refers to the probabilistic measure used in the ACO algorithm. The probabilistic measure was calculated using the equation below (Selvi & Umarani, 2010):

$$P_{i,j}^{n} = \frac{(\lambda_{i,j})^{\alpha}}{\sum_{j\in N_i^n}^{m}(\lambda_{i,j})^{\alpha}} \tag{1}$$

$P_{i,j}^{n}$ = Transition probability for then n-th ant navigates from node (i) to node (j).

m = Number of iterations that represent ants

$\lambda_{i,j}$ = Pheromone trail.

α = Weight value.

The traveling ants are the ones that update the pheromone trails. This corresponds to the number of iterations made for updating the paths to achieve the optimum solution according to the fitness function. The simulation was implemented in MATLAB according to the procedures in the pseudocode below:

Algorithm: Ant Colony Optimization

Initialization of the (ACO) algorithm parameters;

Construction of grid map;

Placement of the obstacles in random coordinates;

Locate point A (starting point); locate point B (destination of the UAVs)

```
If iterate = 1, 2, 3 … N
    For ant = 1, 2, 3… n
        For step = 1, 2, 3 … m
                Find the likelihood (probability) of n-th next … coordinates
                Move to next node location as determined by probability.
                    If the current position is equal to destination
                        Break
                    End
        End
        Keep in memory the distance moved by the n-th ant.
        Calculate the pheromone amount produced by the n-th ant
    End
    Update pheromone concentration for the whole map.
End
Display results.
```

Here's a possible content writing based on the given pseudocode and results:

Pseudocode for the algorithm begins with the declaration of constants and the initialization of variables. There are several constants included in this model: the number of cities, the number of ants, the alpha and beta parameters for the pheromone and distance heuristics, the evaporation rate for the pheromone, and the initial pheromone level. In addition to the distance matrix and the pheromone matrix, there are probability matrices, path matrices, and probability matrices.

The main iteration of the algorithm involves looping for the number of ants, which is set to 500 in this case. Within each ant's loop, there are three nested loops that update the probability matrix, select the next city based on the probabilities, and update the path and pheromone matrices accordingly. These loops implement the ant's decision-making process, which balances the exploration of new paths with the exploitation of known paths.

A pheromone matrix is updated by evaporation and by adding pheromone deposited by the ants after all ants have completed their tours. As determined by the length of the ants' tours, this pheromone update reinforces the paths used by the best ants.

The code that implements this algorithm was tested on a set of benchmark instances and produced results that were compared with the Genetic Algorithm (GA) approach used by (Mirjalili et al., 2020) for the same instances. The results showed that the ACO approach found better solutions than the GA approach in most cases, especially for large instances. The Traveling Salesman Problem is a well-known combinatorial optimization problem that is NP-hard. This demonstrates the effectiveness of the ACO algorithm.

3.1 Path Planning for multiple UAVs

Drone technology is enabling a greater number of UAVs to be deployed simultaneously at the same time. As a result, separate paths may be required for the UAVs. For instance, the case may be illustrated using a simple scenario of two available paths such that the likelihood that a given UAV encounters an adversary along a path 'i' is represented by π_i; in the event that a UAV encounters an obstacle (adversary) the probability that it becomes neutralized becomes 1.

Considering dual methodologies for path planning in unmanned aircraft systems, the subsequent two strategies can be employed.

The first approach centers on a unified routing system. Here, both UAVs follow an identical trajectory, culminating in a probability of reaching the desired location, symbolized as $1-p_1$. Notably, p_1 encapsulates the chance that neither UAV attains the end goal, as highlighted by (K. Li et al., 2020). Conversely, the secondary approach emphasizes diverse routing. Here, each UAV is designated a unique trajectory. The cumulative probability that both vehicles converge at the intended location arises from the combined probabilities associated with individual non-reachability along their respective routes. This is likelihood is written as $(1-p_1)(1-p_2)$. Since $p_1 >0, p_2 >0$ and $p_1<1, p_2<1$, then the product $(p_1 p_2)$ which is the likelihood that no UAV reach the target is less than$1-p_1$. This pattern suggests that when UAVs embark on separate routes, their propensity to face challenges or obstacles amplifies, a perspective resonated by K. Li et al. (2020).

Based on the assessment, when consistent arrival at the destination is uncertain for UAVs, the alternative strategy proves more viable for mission success. This is underscored by the reduced probability of UAVs failing to reach their end goal. The rationale is straightforward: allocating distinct routes to the UAVs diminishes their risk of detection by potential threats in the environment.

Panda et al. (2020) proposed a path planning approach for a single vehicle with multiple possible paths. The planning process is sequential, with penalty weights added to the previous UAV's path to avoid traversing the same cells. In a grid-based spatial layout, cells once crossed by a UAV incur a significant penalty, leading other UAVs to bypass them. A four-step algorithm is used for this approach. The first vehicle's path is planned based on a probability map. The second step is to add a penalty to the cells along the path generated for the first vehicle, resulting in a new map. The third step involves path planning for the second UAV based on the updated map. Finally, these three procedures are repeated for each subsequent UAV (Huang et al., 2023).

Yao et al. (2015) simulated this planned path in a 30 by 30 spatial system represented by square cells. Random values were uniformly produced across five simulation zones, and P(S_i) values were calculated using equation vi. The cell at coordinates (30, 30) was designated as the origin, with the target at coordinates (3, 5) marked with an asterisk. The regions with darker shading are more dangerous and have higher P(S_i) values, as shown in the diagram below. This approach provides a practical solution for optimizing path planning in multiple UAV scenarios and minimizing the risks associated with traversing hazardous regions.

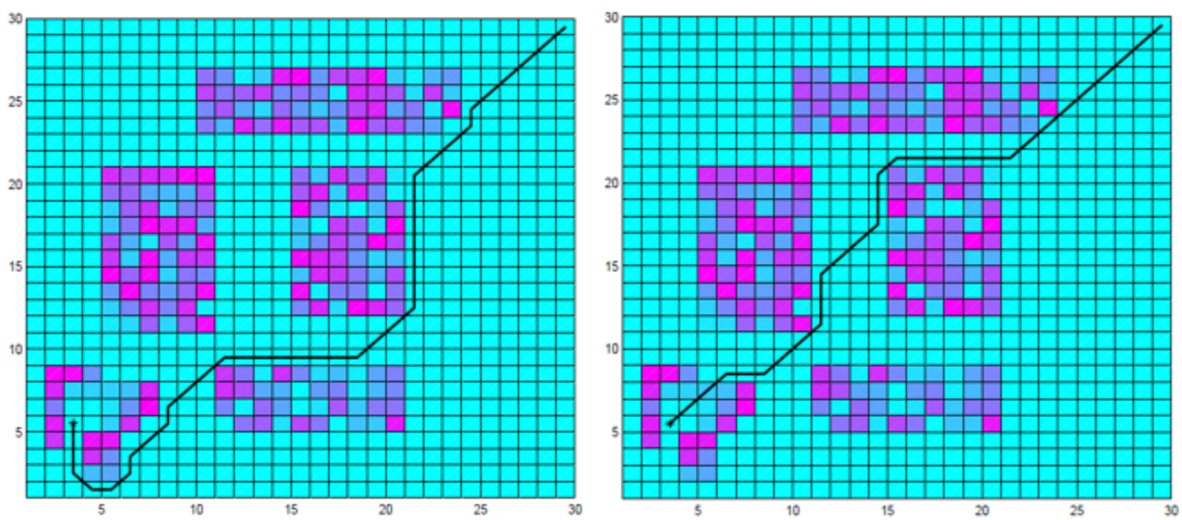

Figure 1 a: Unpenalized results on the left, penalized results on the right.

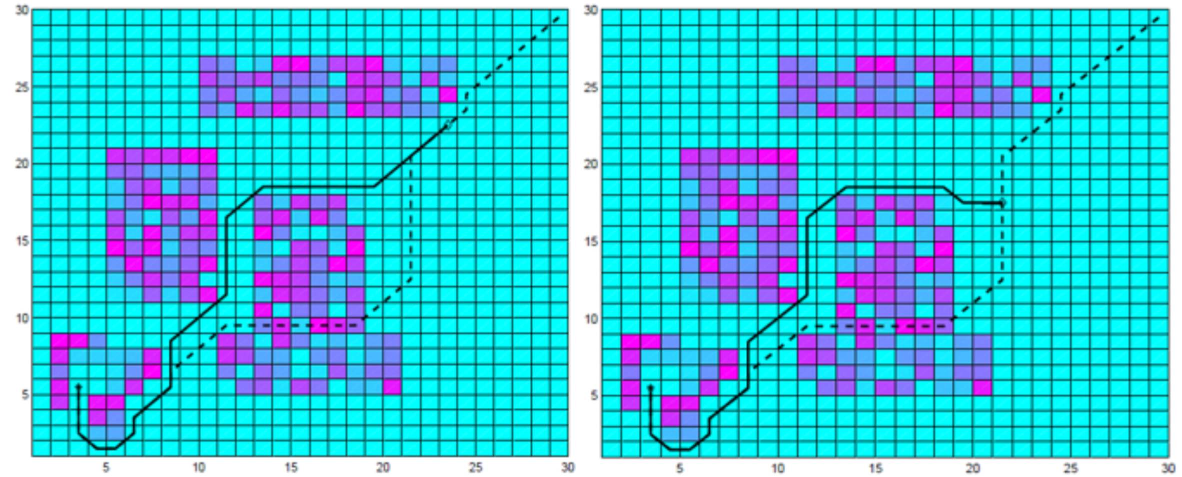

Figure 1 b: Navigation path of UAV during alteration in probability map for both cases

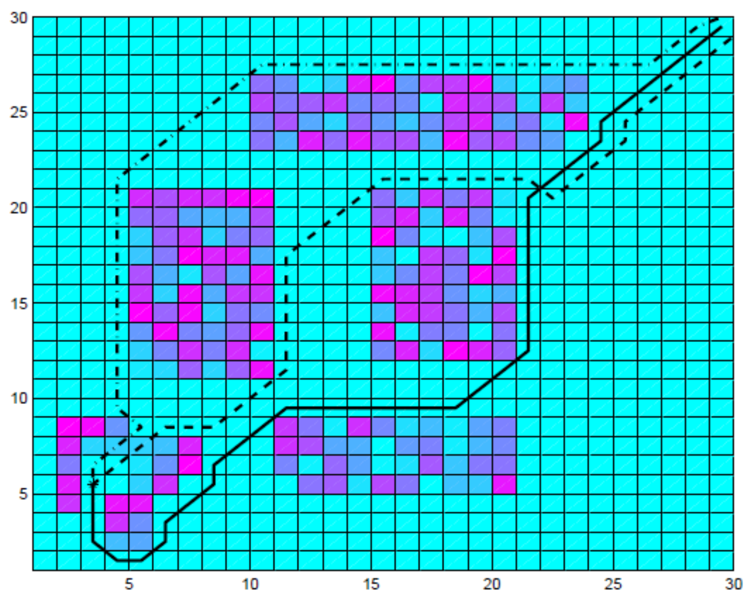

Figure 1 c: Paths taken by multiple UAVs during deployment.

Figure 1a shows the results of the simulation conducted by (Yao et al., 2015). On the left side of the figure 1 c the results of the simulation when a weight of 6 was used, producing the safest path within the spatial system. The path deviates from the darkened grids, which represent high-risk zones, resulting in a non-straight path. This approach ensures that the UAV avoids the most dangerous regions and follows the safest possible route. On the right side of Figure 1a, the same probability map was used with a different approach, utilizing a weight specified by the expression below. This approach produces a straighter path than the previous method, as seen in the diagram. However, it still avoids the high-risk regions to ensure the safety of the UAV. Both methods demonstrate the effectiveness of the path planning approach proposed by (Schwarting et al., 2018), as they successfully navigate through a complex spatial system with hazardous regions. The ability to avoid danger zones and navigate the safest path is crucial for the success of missions involving multiple UAVs, and this approach provides a practical solution to optimize path planning and minimize risk.

$$d_{ij} = \begin{cases} -\log\left(P\left(S_j\right)\right) + c \\ \infty \end{cases} \tag{2}$$

The weight link equation (2) used in the right-hand side of Figure 1a includes a constant real number c, which was adjusted to c=0.1 after modifying the path equation. Comparing the two diagrams, the right-hand side result shows the shortest path while still avoiding the high-risk regions. This approach provides a more efficient solution for path planning in complex spatial systems with multiple possible paths.

In Figure 1b, the results obtained by Kapadia et al. (2016) depict a scenario involving dynamic obstacles, represented by a diamond sign in cell (23, 22). The UAV on the right-hand side shows a deviation from the original path after a change in the probability of cell (23, 22) was detected. To avoid the obstacle, the UAV followed the solid line instead of the dotted path. In a scenario where multiple UAVs are deployed, the first vehicle follows the solid line, the second UAV follows the dashed line, and the third vehicle follows the dotted line. These paths were produced based on the sequence of deployment and the probability map. Overall, these approaches demonstrate the importance of path planning in ensuring the success of missions involving multiple UAVs. The ability to adapt to changes in the environment, avoid obstacles and navigate the safest possible path is crucial for minimizing risks and achieving mission objectives.

Queuing theory models

Queuing theory models are a crucial analytical tool used in the optimization of air traffic problems, telephony networks, and other scenarios that involve queues or waiting lines. In air traffic control, queuing theory is used to grant permissions for take-off and landing, as well as booking-related activities. The theory is also applicable in modeling the path for multiple UAVs (Z. Zhang et al., 2019) .

To understand the application of queuing theory to UAV path planning, it is essential to review its characteristics. A queuing system consists of three main attributes: the arrival characteristics, waiting line, and service facility. The arrival characteristics refer to the input sources that generate arrivals to the service system. It has three primary attributes: the behavior of arrivals, the size of the calling population, and the pattern of arrivals (H. Zhang et al., 2023).

Behavior of arrivals describes the time interval between customers or arrivals according to a probability distribution. The size of the calling population represents the number of customers that are waiting in the queue, which could be finite or infinite. The pattern of arrivals refers to the randomness or predictability of the arrival process.

In the context of UAV path planning, the arrival characteristics could represent the probability distribution of the UAVs' arrival time and location. The waiting line could represent the queue of UAVs waiting to reach their destination, while the service facility could represent the path planning algorithm used to guide the UAVs towards their target. Overall, queuing theory provides a valuable framework for optimizing UAV path planning, enabling efficient resource allocation and reducing waiting times for multiple UAVs. Researchers and practitioners can develop effective path planning strategies for UAVs by modeling arrival characteristics, waiting lines, and service facilities in a variety of scenarios.

The behavior of arrivals in a queuing system refers to the properties of the input to the system that describe the events of the input in relation to the queue. In an ideal case, the inputs or subjects wait in the queue until they are served. However, in practical situations, such as serving arriving passengers at an airport, some behaviors, such as jumping the queue, may occur. Some subjects may fail to join the queue, which is known as balking, while others may join the waiting line but eventually leave before being served, referred to as reneging.

In the system, the size of the calling population determines how many subjects arrive each time. The arriving rate may be unlimited or limited. Finite calling refers to the arrival of subjects that involve a countable number, unlike unlimited arrival. The pattern of arrival describes the schedule of the arriving subjects. For example, a given number of drones may be arriving into a controlled space at a given time. A random arrival is also possible if the arrivals of the subjects are independent of each other. In queuing models, the arrival is approximated using probability distributions. Poisson or exponential distribution is commonly used in describing the arrival rate.

By considering the behavior of arrivals, size of the calling population, and pattern of arrivals, queuing theory can be used to optimize path planning for multiple UAVs. This framework can help researchers and practitioners develop strategies to manage the arrival of UAVs, reduce waiting times, and ensure efficient resource allocation.

$$P\ (n;t) = \frac{(\lambda t)^n}{n!}\ e^{-\lambda t} \tag{3}$$

'n' queuing theory, the variable n is set for integers such that n = 0, 1, 2… which represents the number of arrivals per unit time. P(n;t) is the probability of n arrivals, where lambda is the average arrival rate.

In the case of an unlimited population, models like exponential arriving rate or Poisson's arriving rate can be used in modeling exercises. Waiting lines are parts of a queue system, and their length can be either unlimited or limited. A limited queue line cannot expand to become infinite due to physical law or restrictions, while an unlimited waiting line has no restrictions on size.

In planning UAV paths, queue discipline is another vital attribute of a waiting line, which describes the rules by which subjects receive their service. For instance, First-In-First-Out (FIFO) is a common rule in most queue systems. However, the FIFO system is not applicable in emergency cases (Jayaweera & Hanoun, 2020).

The service facility has two attributes: configuration and pattern of the service system. The classification based on the queuing configurations of the system is in terms of the number of servers, channels, and the number of service stops, among others. In the spatial system of UAV path planning, the cubes for a 3D system represent service points. This is due to the fact that the probability of an adversary encountering a vehicle in space occurs at the cubes.

In summary, queuing theory provides a framework for optimizing path planning in the spatial system of UAVs. By considering attributes such as arrival characteristics, waiting line, and service facility, researchers and practitioners can develop effective strategies to manage the arrival of UAVs, reduce waiting times, and ensure efficient resource allocation.

In queuing theory, models of queuing systems are identified using Kendall notation. The Kendall rules define the arrival patterns and distribution of service time (Voznak et al., 2011). The notation comprises three common letters of the alphabet used to describe the arrival pattern. The letter A denotes inter-arrival time distribution, while the letter B denotes service time distribution. Other symbols that fall under A and B are M, D, Ek, and G, which denote exponential, deterministic, Erlang of order k, and general, respectively.

The exponential distribution is commonly used to model inter-arrival times, while the service time can be modeled using a variety of distributions, such as exponential, deterministic, or Erlang of order k. The general distribution, denoted by the letter G, is used when the service time cannot be modeled using any of the other distributions. By using Kendall notation, researchers and practitioners can identify the appropriate queuing model for a given scenario and optimize the path planning for multiple UAVs. This framework can help manage the arrival of UAVs, reduce waiting times, and ensure efficient resource allocation in a spatial system.

Three dimensional Path planning Algorithms

In the previous section, we discussed how queuing theory can be used to describe the arrival of items into a system, queue behaviors, and service time. Implementing queuing theory can be done using various algorithms that are commonly used in various applications. The evolutionary computational strategy, commonly known as numerical optimization techniques, is often used in path planning for multiple robots (Song et al., 2020).

The common algorithms applied to path planning for autonomous vehicles include the Genetic Algorithm (GA), Particle Swarm Optimization (PSO) algorithm, and Ant Colony Optimization. The paradigm employed in these algorithms in path planning is called the multiple Traveling Salesman Problem (mTSP). The principle operation of the TSP is that more than one salesman is permitted to form part of the solution. Multiple single UAV path planning problems are solved by determining the sequence of visiting the desired regions. Genetic algorithms and Ant Colony algorithms are discussed below.

GA is a typical evolutionary algorithm applied in numerous optimization problems such as UAV path planning and so on. The algorithm works like a natural biological system that involves information transfer in genes, hence the name. The Genetic Algorithm involves three main parts in its execution time, namely natural selection, crossover, and mutation. GA works in three stages (Okwu & Tartibu, 2021):

1. Initialization: The initial population is generated randomly, usually with a specified number of chromosomes.
2. Selection: The most fit chromosomes are selected based on fitness evaluation criteria, such as the highest fitness score or lowest cost.
3. Crossover and Mutation: The selected chromosomes are used to create new offspring by combining the genetic information using crossover and mutation operators. The offspring then form the next generation of the population, and the process is repeated until a satisfactory solution is found.

ACO is another algorithm that is widely used in path planning for multiple UAVs. It is inspired by the behavior of ants in their search for food. ACO involves three main components, namely the ants, the pheromone, and the environment (Rokbani et al., 2021). The ants leave a trail of pheromone as they move, and the pheromone is used by other ants to follow the path to the food source. The algorithm works by simulating this behavior in the search for the optimal path (X. Zhou et al., 2022).

By utilizing evolutionary algorithms such as GA and ACO in path planning for multiple UAVs, resource allocation can be optimized, waiting times can be reduced, and arrivals can be managed efficiently. These algorithms offer a promising approach to solving complex optimization problems in spatial systems. In the optimization process, the algorithm generates solutions, also known as chromosomes, through an iteration process. Each chromosome is updated according to the fitness function, and the best-fit chromosome is selected to appear in the next generation.

Mutation is not random but rather stepwise, at a rate of one percent or a mutation rate of 0.01. This means that, in the crossover population, one percent undergoes mutation. For example, if thirty chromosomes are produced, each with six bits, then the bits mutated are determined by $30 \times 6 \times 0.01 = 1.8$, which is roughly 2 bits (Brand et al., 2010).

As a result of the GA process, the generated solutions are updated according to the fitness function, and the best-fit chromosome is selected to appear in the next generation. Crossover and mutation are used to achieve diversity and optimize the solution space. The application of the Genetic Algorithm in UAV path planning can help optimize resource allocation and reduce waiting times, ensuring efficient and safe operation of multiple UAVs.

Ant Colony Optimization

Ant Colony Optimization is another optimization algorithm that imitates the travelling salesperson paradigm of optimization. Similar to evolutionary algorithms, it mimics the social attributes of an ant system, where travelling ants leave a trail of substance that guides them in their path. The substance, pheromone trail, acts as a feedback system that guides future ant movements towards the most efficient path (Dai et al., 2019).

ACO is useful in finding an optimal path and is commonly applied in telecommunication routing path finding, among other numerical optimization problems. Its application is similar to PSO and is, therefore, chosen for application in this study. In the context of UAV path planning, Ant Colony Optimization can be used to optimize the path selection process, considering factors such as avoiding high-risk areas and minimizing travel time. The algorithm can help improve the efficiency and safety of multiple UAV operations in a spatial system, ensuring that resources are optimally utilized while minimizing waiting times.

3.5 Proposed Model

The problem at hand involves 3D path planning for UAVs arriving in a space governed by exponential distribution rules. Each UAV enters at location A, defined by coordinates, and aims to reach point B, also specified by coordinates. This particular issue involves the presence of obstacles, which may cause collisions if an inadequate path is chosen between the two points. As a result, optimization rules are appropriate for addressing this problem. It's important to note that air flow speed is not considered in this scenario, and the simulation will be conducted for a predetermined duration. Additionally, each cube serves as a service center according to queuing theory. Probability functions are employed to determine the optimal path in this context.

Let's consider space below;

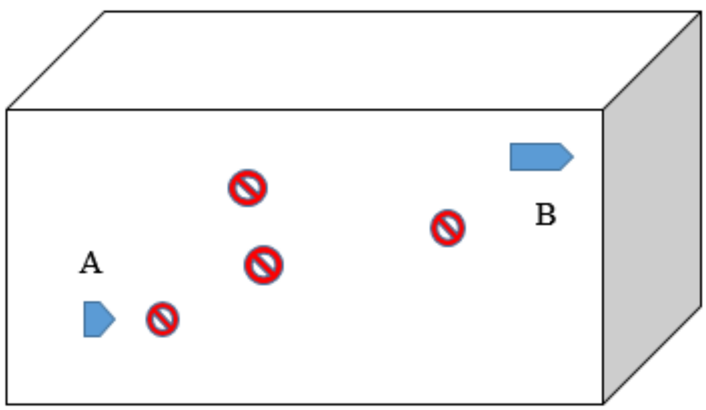

Figure 2a: Sketch for showing starting point and destination of the UAVs.

The figure 2 a presents a regulated space featuring an arrival point, denoted as A, for the UAVs and a destination, designated as point B. Scattered between these two points are red hazard markers representing threats that the UAVs must circumvent. As discussed in the literature review, these markers are randomly generated to ensure a high probability of collision, which the UAVs must avoid. Additionally, the speed of the UAVs is controlled to prevent collisions among the vehicles themselves.

To solve this problem, this study proposes to use the ACO algorithm implemented in MATLAB software. A model representing the proposed solution can be observed in figure 2 b.

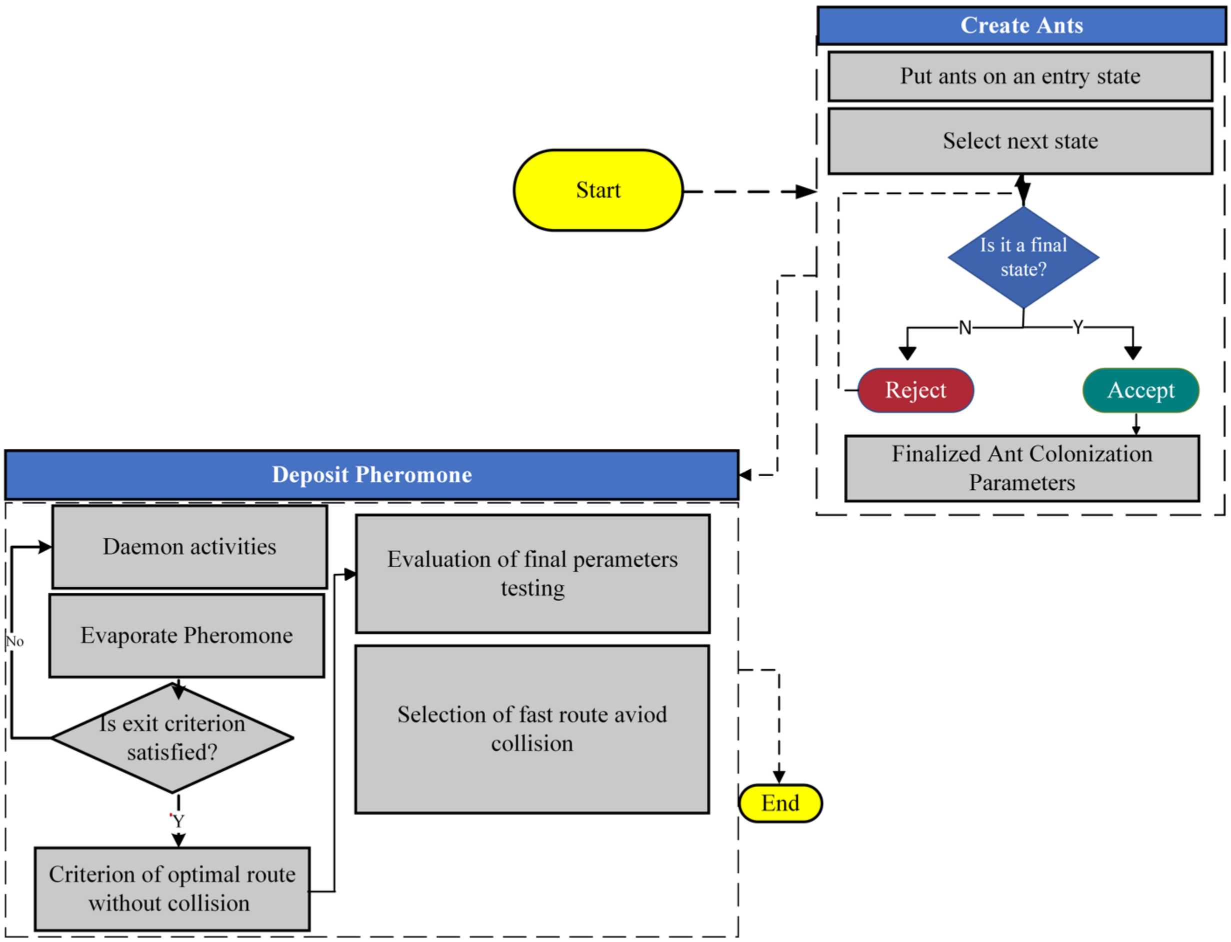

Figure 2b: Ant Colony Algorithm flow chart for supply chain optimization.

4. Results and Discussion

This study implemented the ACO algorithm to determine the paths taken by UAVs between their origin and destination multiple supply chain points. The starting point A (0, 0, 0) signifies the entry cubicle where all UAVs enter the system, and the endpoint B (20, 20, 0) marks the destination. Between points A and B, circular obstacles were generated using the ezplot function, featuring a unit length radius. In the controlled space, a total of fourteen obstacles were created.

These obstacles were assigned threat values based on equation iv from graph theory. Figure 3a provides a graphical representation of the generated obstacles between supply chain route.

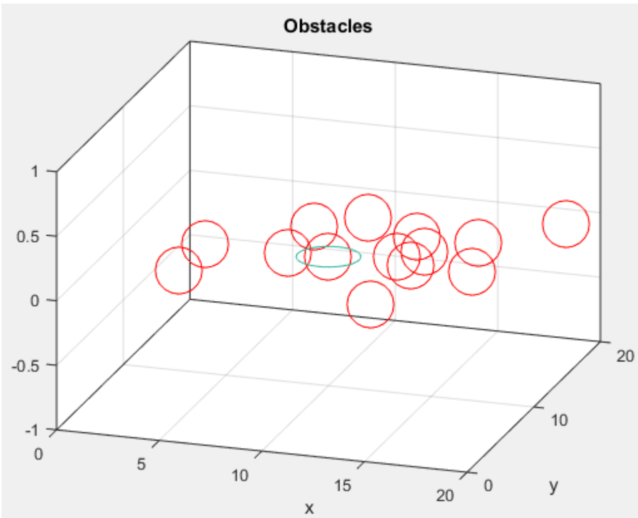

Figure 3a: Threats between the starting point and the destination.

The fourteen obstacles, produced using the ezplot function, pose risks to the UAVs, which must avoid traversing through their coordinates within the supply chain network. In the metaheuristic optimization process for the UAV path, these points introduce penalties. Consequently, while converging towards the supply chain destination points, the UAVs circumvent these coordinates and opt for the nearest path. Figure 3b illustrates the path taken by UAVs from origin to destination of the supply chain network represented by the blue line.

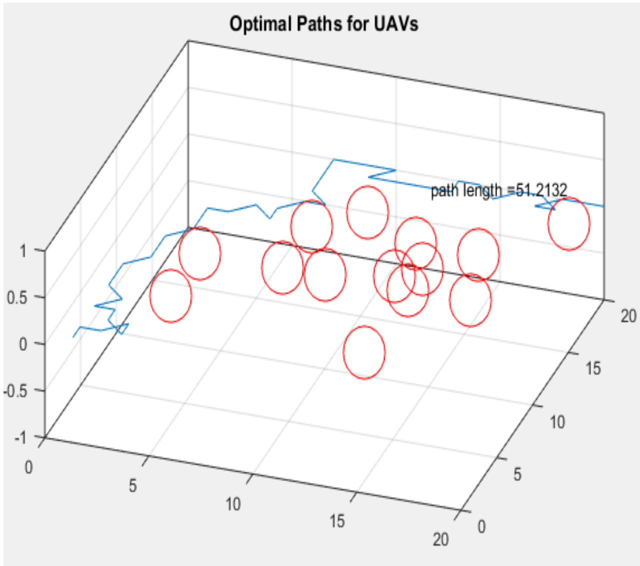

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Figure 3b: UAVs path between supply chain point A and point B.

Despite deploying numerous UAVs resembling ants, a singular route was taken between supply chain points A and B, influenced by the obstacle layout. This route was determined by a safety factor, bypassing coordinates with heightened penalties. Pheromone trails served as indicators for secure delivery routes, highlighting areas with dense pheromone presence. For instance, Figure 3c showcases these trails, with lines marking feasible routes. The color scale indicates that a more yellowish tint relates to denser pheromone levels, indicating safer navigation zones. Such trails present various alternate routes for other UAVs, minimizing risks of congestion or collisions.

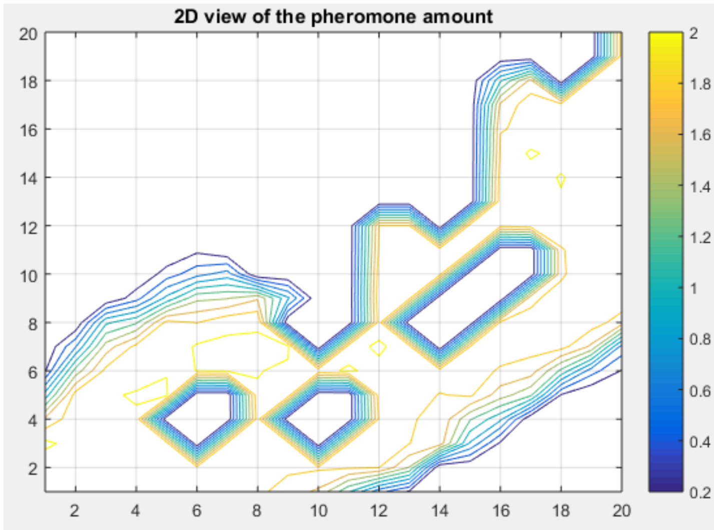

Figure 3c: Two Dimensional view of pheromone trails of supply chain route.

In the queuing framework, spatial cuboids act as service hubs, and UAVs are attracted to those exhibiting elevated pheromone levels. It is interesting to note that the maximum concentration reached two units as a result of the pheromone decay factor, which represents the best solution for pathway planning. The three-dimensional distribution of pheromone concentration is depicted below.

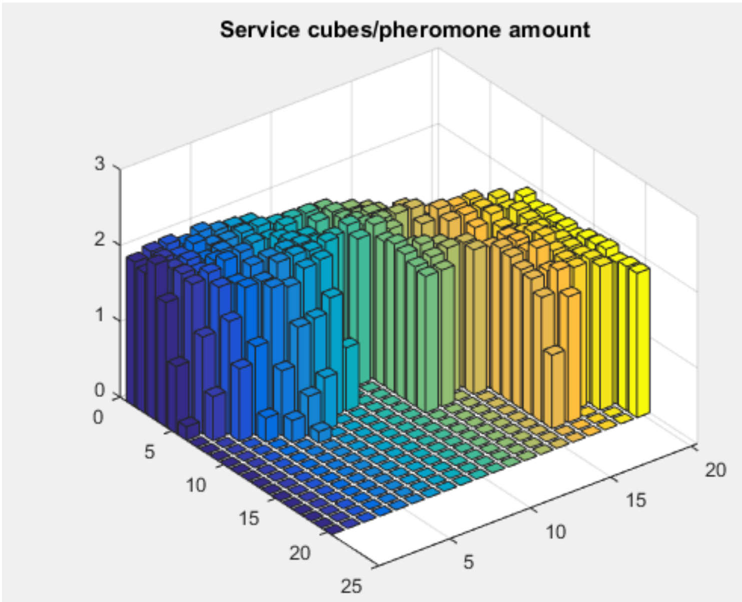

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Figure 3d: 3D supply route based on pheromone trail

The outcomes from our study were compared with findings from other experts in the field. A study by Peng and colleagues in 2015 integrated the Lyapunov Guidance Vector Field (LGVF) with Interfered Fluid Dynamical Systems (IFDS) to facilitate real-time UAV navigation, ensuring obstacle evasion in threat-laden terrains. This blended strategy outperformed the standalone techniques. Notably, the metrics in their research varied, encompassing a singular unit sampling time, a set cruise speed of 0.15, specific repulsion range parameters, a planning step spectrum from 1 to 10, among other unique factors.

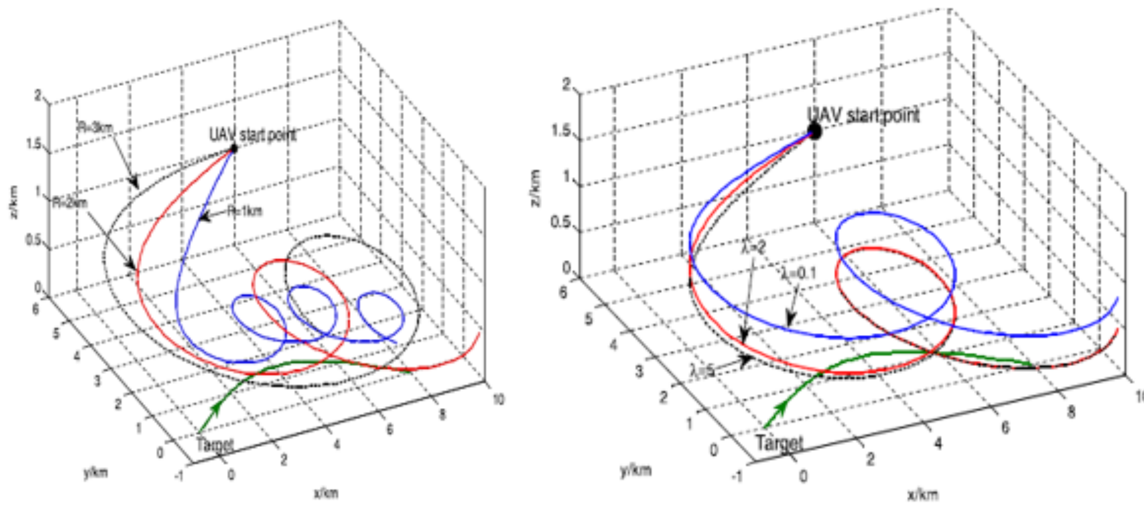

Figure 3e: Different expansion parameters and detection radius values for LGVF + IFDS

The combination of LGVF and IFDS for path planning yields better outcomes than genetic algorithms. This is clear as the created routes are unique, ensuring safe delivery from point A to B without any collisions.

4.1 Theoretical Implications

This study leads to significant theoretical advancements in multiple domains like supply chain management, robotics, optimization algorithms, and cybersecurity. The interdisciplinary nature of this approach may enable more cross-domain research, which could result in innovative solutions to complex problems. The ACO and IFDS-LGVF algorithms' implementation and their comparison could lead to new developments or modifications in path planning algorithms, increasing their efficiency or suitability for different scenarios.

UAVs could revolutionize how we perceive their role in global supply chains as they are used as part of global supply chains. If successful, this could expand the theoretical understanding of UAV applications and drive further research in this area.

Security and privacy concerns in UAV usage could be addressed by developing a framework in the area of cybersecurity and information systems. This could guide future practices and policies around UAV usage and data management.

4.2 Managerial Implications

This study provides managerial applications to industries and managers. Managers could use the findings from this study to formulate strategies for implementing UAVs in their supply chain operations. The comparison of different path planning algorithms would provide an understanding of what could work best for their specific scenarios, thus aiding strategic decisions.

The study provides insights into potential cost savings from using UAVs, which would help managers make informed budgeting decisions. The study's findings on security and privacy considerations could help managers understand the associated risks and develop risk mitigation strategies, including data protection policies and physical security measures. Managers could leverage the findings to improve process efficiency, such as reducing delays in supply chain operations by adopting UAVs, thus leading to improved service quality and customer satisfaction. Understanding the technology and its implications would allow managers to train the workforce better and manage changes effectively.

4.2.1 Specific Action Plans:

- Managing multiple UAVs effectively in a supply chain requires managers to develop strategies to ensure collision-free functioning. This includes the selection of appropriate path planning algorithms, infrastructure development, and staff training.
- There is a necessity for managers to plan and budget for investments in UAVs and related technologies, including data management systems and security infrastructures.

- It is crucial for managers to establish and implement risk mitigation measures. These should include data protection policies, physical security procedures, and emergency response strategies to handle potential issues effectively.
- Managers should devise comprehensive policies related to UAV usage, encapsulating operational guidelines, safety protocols, and data management practices to ensure smooth operations.
- Lastly, managers should actively engage with regulatory bodies to advocate for policies that enable the use of UAVs in supply chain activities, whilst also prioritizing privacy and security concerns.

5. Conclusion and Recommendations

This study developed a 3D path planning method using queueing theory to address the importance of UAVs in sustainable supply chains. The aim of this research is to enhance UAV navigation between two locations in a spatial setup, where their entry follows a growth rate. The primary focus was guiding UAVs from point A (0, 0, 0) to point B (20, 20, 0) using a Cartesian framework, updating regularly at set time periods. To achieve our goal, we incorporated queuing theory and compared the performance of two evolutionary algorithms. The first algorithm we employed was the ACO, which simulates the movement of ants navigating around obstacles to find the optimal solution corresponding to the destination coordinate. The second algorithm was a hybrid of LGVF and IFDS algorithms. This hybrid approach utilizes a fluid motion analogy to solve optimization problems.

Our results showed that both ACO and the LGVF-IFDS hybrid approach were effective in optimizing the 3D path planning for UAVs traveling between the two points. However, the LGVF-

IFDS hybrid approach outperformed ACO in terms of optimization efficiency and computational time.

This research contributes to the advancement of sustainable supply chains by offering a comprehensive and effective 3D path planning method for UAVs. This study provides valuable insight for future researchers and practitioners in UAVs and logistics by incorporating queueing theory and comparing two evolutionary algorithms.

The current study may rely on certain simplifications in the queuing theory and ACO models, which may not fully capture real-world complexities. The model may assume a static environment with fixed obstacle positions, while actual conditions might involve dynamic obstacles or changing conditions that affect UAV navigation. The study may focus on a specific type of UAVs or a narrow range of supply chain applications, limiting the generalizability of the results to other UAVs or broader supply chain scenarios. The ACO algorithm can be computationally intensive, especially when scaling up to larger problem sizes or more complex scenarios. Privacy and security concerns: Future research may address privacy and security implications associated with the use of UAVs in supply chains.

Developing models that account for dynamic environments and real-time changes in obstacle positions, weather conditions, or airspace restrictions could improve the applicability of the results. Investigating other optimization techniques, such as Particle Swarm Optimization, Genetic Algorithms, or Reinforcement Learning, to compare their effectiveness in UAV path planning and supply chain optimization. Exploring the applicability of the proposed approach to a broader range of UAV types and supply chain scenarios could enhance its practical relevance and increase its impact. Integration of privacy and security measures: Future research could focus on incorporating privacy and security considerations into the queuing theory and ACO models, developing algorithms that ensure the safe and responsible use of UAVs in supply chains. Policy and regulatory frameworks: Examining the effects of existing or proposed policy and regulatory frameworks on UAVs adoption and operation in supply chains, and proposing new policies to support the sustainable integration of UAVs into supply chain management.

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Computers), Guest Editor (e.g., Journal of Cleaner Production, Current Opinion in Green and Sustainable Chemistry) and Reviewer for about 100 journals indexed in Scopus. During its academic career, Idiano D'Adamo published 131 papers in the Scopus database, reaching an h-index of 43. He has participated in scientific research projects (PRIN2022 “Protecting the Environment: Advances in Circular Economy (PEACE)”, PNRR-PE “Made-in-Italy circolare e sostenibile”, Horizon 2020 “Star ProBio”, Life "Force of the Future"), has collaborated with relevant national institutes (MATTM, CNBBSV, SVIMEZ) and has written for major national newspapers (Formiche, il Messaggero). His current research interests are bioeconomy, circular economy, green energy, sustainability and waste management.

Charbel Jose CHIAPPETTA JABBOUR has been appointed as Head of the Information Systems, Supply Chain Management & Decision Support Department and Professor of Green, Circular, and Responsible Supply Chains at NEOMA Business School, France. He is one of dozens of French-based scholars to have been included in the prestigious Clarivate/Web of Science Highly Cited Researcher awards due to having multiple articles ranked among the top 1% of most cited papers globally. His international career includes both teaching and research in Latin America (Brazil), Asia (Japan), and Europe (Scotland, England, and France). He has published articles in numerous top-tier journals according to a wide range of rankings. In 2019, he received a British Academy of Management best paper award in Responsible Management (BAM Conference). He has been an Associate Editor at the Journal of Cleaner Production. He was one of the youngest academics in the history of the University of Sao Paulo (USP) to receive Habilitation in Management. He has served as PI/Co-I of a number of large-scale externally funded research projects, including Innovate UK, Midlands Engine UK, and FAPESP. He has supervised dozens of early-career researchers, both PhDs and post-docs. Charbel Jose is passionate about the application of the latest research in his teaching in the pursuit of creating more responsible future business leaders.