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Optimizing Drone Logistics: A Scoring Algorithm for Enhanced Decision Making across Diverse Domains in Drone Airlines

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Abstract: The complexities of decision-making in drone airlines prove to be pivotal and challenging as the dynamic environment introduces variability and many decisions are conventionally static. This paper introduces an advanced decision-making system designed for the multifaceted landscape of drone applications. Our proposed system addresses various aspects, including drone assignment, safety zone sizing, priority determination, and more. The scoring model enhances adaptability in real-time scenarios, particularly highlighted by the dynamic adjustment. Based on the scenario concerning the definition of the safety zone, we have successfully applied this method and evaluated all potential scores. The user-friendly and intuitive configuration further augments the system's accessibility, facilitating efficient deployment. In essence, the proposed system stands as an innovative approach with decision-making paradigms in the dynamic landscape of drone operations.

Keywords: decision making; unmanned aerial vehicles; logistic drone airline; conflict management; real-time scoring

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1. Introduction

Traditional land-based carriers contribute to issues such as traffic congestion, environmental pollution, and misallocated resources. The integration of unmanned civilian logistics drones offers a promising alternative that not only addresses these challenges but also introduces unprecedented flexibility and efficiency in the transportation of goods. By leveraging aerial routes, drones can navigate directly from point to point, avoiding the constraints imposed by road networks. This not only reduces transportation times but also minimizes the environmental impact, making drone logistics an environmentally friendly and sustainable solution for the evolving needs of the logistics industry [1,2].

In different scenarios, drone airlines operate a fleet of unmanned aerial vehicles (UAVs) for various tasks, ranging from package deliveries to surveillance missions [3]. The provision of spare parts (so-called C-parts) for the industrial sector is an area that stands out due to the handling of particularly time-critical goods. This is because downtime in industrial plants can become costly in a very short time [4]. Additionally, internal logistics involve either the transport of goods within a factory site or the connection of additional areas near the site. Further areas are required when the existing ones are no longer sufficient. Still, the expansion of a company is not possible due to environmental factors such as rivers, roads, residential areas, or regulatory measures. In such cases, shuttle services are necessary to connect the outsourced areas. An intelligent, secure, and interconnected drone airline is therefore a solution to the challenges described in time-critical goods delivery.

However, the efficiency and success of drone airline logistics hinge on effective decision making. Drones rely on automated systems to navigate, manage emergencies, and optimize flight paths [5]. This necessitates real-time decision-making algorithms that can handle complex scenarios and ensure safe, efficient deliveries [6]. This entails allocating tasks and choosing an appropriate drone. Once the task and drone are determined, the selection of a route becomes essential. All these decisions must be made within the operational context of a drone airline. In designing a universal solution, these decisions cannot be simplified to binary; they require a continuous numerical representation for all options, hence referred to as a score. Every decision made by the drone's systems directly impacts the entire operation's success and efficiency [7].

A naive approach involves predefined values for these decisions. Predetermined values before a drone's takeoff can introduce various issues and challenges, such as inflexibility, unfairness, resource wastage, limited adaptability, and safety risks [8]. Predefined values typically rely on static assumptions and data collected before flight, lacking the capability to account for real-time information, such as unpredictable events or changing environmental conditions. Consequently, this can inhibit the efficiency of flight operations and increase the risk of collisions and conflicts among drones, especially in densely populated or complex environments [9].

A more appropriate approach involves utilizing dynamic as well as static parameters to establish appropriate decisions. Addressing variables such as weather conditions, obstacle proximity, and payload weight adds further complexity to the decision-making process. Take the safety zone, for instance: velocity becomes pivotal, as higher speeds reduce drone flexibility, necessitating a larger zone [6]. Similarly, the quality of the network connection is also a crucial factor in defining the size of the zone. A weaker communication between drones delays conflict resolution when drones disrupt each other, increasing the risk of hazardous situations [10,11]. Consequently, incorporating numerous parameters is essential for making decisions in the drone environment to ensure both safety and efficiency. The challenge lies in balancing these diverse elements and developing a general scoring system for enhancing the overall reliability and adaptability of drone operations in various scenarios.

In this paper, we introduce a methodology for the decision making of unmanned civilian logistics drones. This approach is built upon a custom-developed rule-based framework that utilizes dynamic measurements for the scoring computation of many applications, such as task selection, priority in conflicting situations, and the definition of safety zones. Furthermore, this approach is specified by a predefined adaptive system. During the flight, this system can be dynamically adjusted, rendering the entire methodology highly flexible. This allows for customizable computations throughout the entire transportation process. Notably, this approach is characterized by its user-friendliness and only requires expertise in logistics parameters to design the decision-making process. Here, it is crucial to highlight that our primary focus is on the decision-making process itself rather than on subsequent tasks, such as conflict avoidance in air traffic management, that typically involve the development of path-planning strategies. Our contributions can be summarized as follows:

1. The introduction of a method for decision making for unmanned civilian logistic drones in various fields.
2. The specification of a multitude of static and dynamic metrics that contribute to various applications of the scoring algorithm.
3. The flexibility to adjust the calculation throughout the transport process and thus respond to changing conditions or requirements.
4. The emphasis on ease of use, as the approach only requires expert knowledge of logistics parameters.
5. The enhancement of system efficiency and performance by evaluating specific needs and incorporating either frequency-based or event-based approaches for a more adaptive update.

This paper is structured as follows: Section 2 provides a discussion on related work. Section 3 describes domains within a drone airline environment where crucial decision making relies on dynamic as well as static parameters. In Section 4, we present the problem definition and numerous parameters of significance in the context of drones, and introduce our scoring algorithm and the overall framework. The experimental setup is detailed in Section 5, which also includes the evaluation of the approach. Lastly, Section 6 summarizes the contents of this paper and provides concluding remarks.

2. Related Work

In recent years, drones have emerged as a promising technology with applications in a variety of areas, including logistics and supply chain management [12]. However, in the literature, different studies can be found that reveal the importance of the use of drones in the logistics industry, as well as the challenges for their implementation [4,13–15]. The challenges in drone airlines include navigating stringent regulations, optimizing payload capacity, addressing adverse weather conditions, implementing advanced navigation systems, ensuring security, developing dedicated infrastructure, integrating with existing transportation systems, and effectively controlling operational costs. In all of these domains, a common factor emerges: the need for real-time decision making.

In this sense, one of the first decisions to be made is the allocation of tasks, which is crucial in applications employing multiple drones, ensuring effective resource coordination to meet the objectives. Grippa et al. propose a task selection strategy where the first assignment is directed randomly to vehicles and the second assignment is allocated to the nearest vehicles using queuing theory with Poisson processes for modeling and analysis [16]. In a review, Poudel et al. evaluate 27 task selection algorithms, presenting their respective advantages and disadvantages [17]. Despite the nature of these approaches, they are specifically designed for use in certain scenarios and lack the ability to quickly adapt to other applications.

Similarly to task allocation, there needs to be a drone selected for the defined job. This process is explored in detail by various researchers. Grippa et al. propose in their study an initial policy that prioritizes the assignment of the first job to the vehicle with the lowest workload. It follows a first-come-first-serve order, directing jobs to the vehicle with a minimal workload. Conversely, the second policy adopts a different approach by assigning the first job to the vehicle with the least additional workload. Instead of using the current workload, this policy considers the workload added by the new job to the existing workload. The underlying idea is to minimize the overall workload in the entire system over an extended period [16]. Hazama et al. propose a solution using sets of customers assigned to the takeoff points, and a heuristic rule determines the assignment to the drones [18]. Sawadsitang et al. address the problem of drone assignment in the context of a policy of cooperation of providers to share the full cost of the service. For this, they use a mixed integer programming approach and heuristic optimization [19].

Typically, after selecting a drone for a specific task, there are numerous mission fulfillment options, similar to the notion that "all routes lead to Rome". Hence, choosing the optimal route for the drone, considering the task's specific requirements, is crucial [20]. In the low-level path design, the combination of UAV flight constraints with a sparse A* algorithm, along with an enhanced cost function, reduces the search space and shortens the search time [21]. In route network planning, He et al. propose a priority structure to decouple the network planning problem, which is NP-hard, into single-path planning problems. They also introduce a novel space cost function to enable the design of dense and aligned routes in a complex urban environment [2]. Although the collaboration of multiple UAVs effectively addresses area coverage issues, the development of an online approach for multiple-UAV coverage remains challenging due to energy constraints and environmental dynamics.

The increasing use of multiple UAVs has led to a significant focus on developing collision avoidance techniques and algorithms. Various studies, including those by Soria et al. [22], Yasin et al. [23,24], and Jenie et al. [25,26], have contributed to this field. Barfield et al. [27] outline technical requirements for an automatic collision avoidance system, introducing two zones: a de-confliction sphere and an avoidance sphere. Jenie et al. [26] expand on this, proposing a three-sphere structure for a UAV anti-collision system, with static safety zones defined in units of time. Lee et al. [28] employ fuzzy logic for UAV conflict avoidance, using dynamic parameters like distance and angle to generate commands. Ho et al. [29] suggest incorporating additional parameters, such as vehicle type and navigation device accuracy, into safe zone calculations. However, these approaches often focus on either dynamic or static parameters, with limited emphasis on combining both or incorporating semi-static measurements that possess static characteristics but can be adjusted during flight.

In the domain of drone prioritization, the current research underscores the necessity for refining guidelines, especially when conflicts arise within specific use cases. Alarcón et al. [30] propose an initial prioritization based on mission types, recognizing the need for further refinement in the face of conflicts. Jover et al. [31] classify prioritization into eight classes, ranging from medical emergencies to leisure flights, providing a broad framework that requires additional refinement for conflicts within the same use case. Alharbi et al. [32] adopt a simplistic approach with random priorities, revealing impracticality in real-world scenarios due to a lack of consideration for critical drone performance factors. López et al. [33] introduce a speed- and location-based prioritization system, offering improved granularity but with limitations in considering broader influencing parameters. Fu et al. [34] expand the factors influencing prioritization by introducing operational costs, maintenance costs, flight power, and battery level. Ribeiro et al. [35] emphasize various parameters for priority determination, adding depth to understanding but lacking a comprehensive algorithm to integrate these into a unified framework. The existing literature highlights the need for a more sophisticated and context-aware approach to drone prioritization that considers dynamic and device-specific priorities while incorporating an algorithm for information aggregation.

In our approach, various input parameters, both static and dynamic, are considered with the objective of decision making. What sets our approach apart is the development of a universal algorithm applicable across diverse applications, including static logistics, semi-static trajectory planning, and dynamic safety decisions. Our approach also takes into account the sampling characteristics of the diverse applications, making it callable either on an event or frequency basis. This user-friendly solution eliminates the need for expertise in mathematics or related fields. Unlike many researchers, our methodology incorporates both expert knowledge and real-time sensor measurements. Another notable distinction lies in the adaptability of our algorithm. While others utilizing static parameters remain fixed, ours is online-adaptable. This adaptability provides versatility, enabling its utilization across different domains based on specific requirements.

3. Challenges in Drone Logistics

In the realm of drone logistics, we are confronted with the intricate task of harmonizing expert knowledge with real-time sensory data to construct a decision-making framework. In a scenario wherein a multitude of interconnected drones operates, our work centers on developing a rule-based decision-making algorithm adept at considering various parameters, including, i.e., package importance (static) and drone battery levels (dynamic) [36]. Outlined herein are distinct challenges, depicted in Figure 1, in drone logistics, to the operational demands of an airline encompassing multiple unmanned aerial vehicles (UAVs) [37]. These challenges can be classified into three categories: logistical challenges, traffic management challenges, and safety challenges. What connects these applications is their reliance on an algorithmic framework that combines diverse parameters into a cohesive metric [36–38]. However, the complexity amplifies within a multimodal environment including trucks and other participants, necessitating a system with a high degree of generality and adaptability to accommodate the demands. For simplicity, our emphasis is particularly on delivery drones.

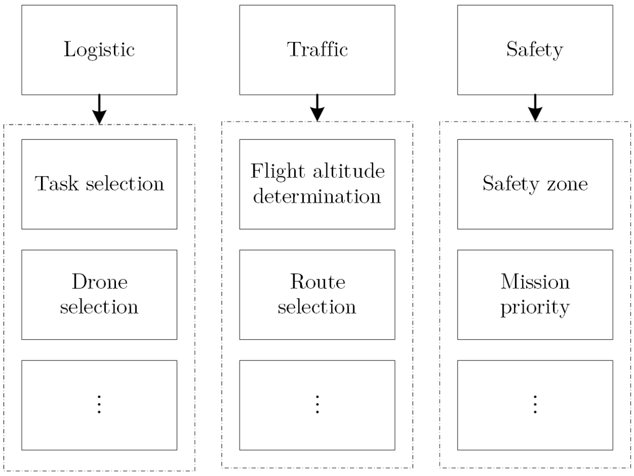


Figure 1. Examples of diverse challenges of the decision-making algorithm, classified into logistical, traffic management, and safety.

In the subsequent section, we present an overview of the drone airline concept. We then delve deeper into the challenges associated with its application as depicted in Figure 1, exploring the intricacies of its integration.

3.1. Drone Airline

The configuration of the drone airline comprises a set of interconnected elements that enable the efficient and safe operation of a transportation system. In the basic scenario, three main elements stand out: a base station, multiple drones, and a communication network. Figure 2 shows the basic scenario [39].

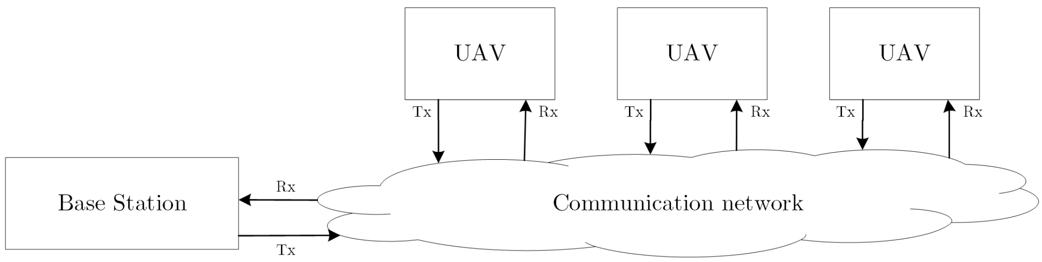


Figure 2. Drone airline scenario with three components: base station, numerous drones, and a communication network.

The communication network plays a pivotal role in facilitating interconnection among multiple drones and the base station within a drone airline. It enables seamless data transmission among the drones themselves and between them and the base station, thereby facilitating the efficient coordination of aerial operations. Furthermore, the communication network empowers the decision-making algorithm, designed to address diverse categories of challenges, to be enriched with parameters from various components of the airline's infrastructure [40,41].

The multiple drones within the airline constitute the primary component. Thanks to onboard sensors and their communication system, the drones feed the decision-making algorithm with highly dynamic parameters, such as speed, position, altitude, battery status, etc., rendering them ideal for tackling safety challenges such as defining safety zones or determining drone priorities [40,41].

Lastly, the base station stands as a key component in the infrastructure of a drone airline as it typically harbors the highest computational capacity within the system and provides a range of essential services for the safe and efficient operation of the drone fleet. These services include fleet management, communication, maintenance, and storage. Additionally, it can furnish a user interface for operators to monitor drone location and status, send control commands, and download sensor data [41–43].

3.2. Logistical Challenges

Logistics challenges generally require decisions to be as stable and consistent as possible, maintaining a minimum level of variability over time, and, by their very nature, offer stability and predictability. Consequently, logistical challenges primarily rely on static data from the base station and rarely require active communication. However, this advantage comes at the cost of limited adaptability. Once a decision has been made, changing it is not beneficial due to factors such as exponentially increasing costs or other constraints. For example, consider the scenario where a drone is assigned a specific package. Mid-flight changes by returning to the base and changing the load are not advisable due to the significant increase in operational costs. Similarly, in the field of drone selection, once a specific drone is chosen for a mission, its characteristics remain fixed throughout the flight. In the next sections, we will discuss examples from Figure 1 that demonstrate the challenges of logistical decision making in drone airlines.

3.2.1. Task Selection

The first step of a drone airline involves the selection of cargo for transportation. A notable challenge lies in determining the specific cargo that deserves priority for delivery [44]. Traditionally, the approach follows a 'first come, first served' model [16]. However, within the logistical context, various scenarios may arise where the priority needs adjustment. For instance, in an industry experiencing an unforeseen production line downtime due to sensory issues, the urgent delivery of replacement sensors becomes essential. This prioritization hinges on several factors, including the significance of the cargo or the operational costs. Establishing clear objectives is the foundational step in developing an effective drone delivery system [45]. The objectives serve as the guiding principles, outlining the desired outcomes of the system. These might encompass optimizing delivery times, minimizing operational costs, and ensuring the efficient handling of varying payload sizes and types [46].

3.2.2. Drone Selection

In the realm of drone logistics, similar to the selection of tasks, the choice of the right drone for a defined mission presents a challenge. Selecting the right drones involves a meticulous examination of technical specifications. These specifications, encompassing payload capacity, range, speed, and battery life, serve as the framework for ensuring that the chosen drones align with the identified tasks [47,48]. Apart from the technical specifications, there is also an option for the type of drone. The choice between multirotor and fixed-wing drones depends on the nature of the tasks and operational requirements. Multirotor drones might be ideal for short-distance deliveries within urban areas, providing agility and flexibility. In contrast, fixed-wing drones excel in covering longer distances efficiently, making them suitable for extended delivery routes [49]. Additionally, safety is a paramount consideration in drone operations. Beyond meeting regulatory requirements, ensuring that selected drones comply with safety regulations and standards is crucial. Implementing features such as collision avoidance systems, redundancy in critical components, and adherence to industry safety standards collectively contributes to a secure and reliable drone fleet.

3.3. Traffic Management Challenges

For the traffic management challenges, a higher degree of variability is desired in decision making than in the case of decisions for logistical challenges. The emphasis here is on the balance between stability and adaptability; these decisions are often established and maintained over long periods because of their effectiveness or efficiency. However, they are not entirely inflexible. In the presence of significant environmental perturbations that challenge the underlying assumptions or the efficacy of the decision, the decision may be re-evaluated and potentially modified. Therefore, these decisions are primarily made statically at the base station, but they can also communicate with the participants during events and adapt accordingly. To illustrate the complexities of decision making for these types of challenges in the context of drone airlines, we turn to the specific examples presented in Figure 1. The following sections will discuss these scenarios and highlight the challenges.

3.3.1. Route Selection

Within delivery systems, a multitude of routes are available that are proposed by the flight management system. The selection of the most suitable route is contingent on numerous parameters. Notably, the efficiency of a drone delivery system relies heavily on the overarching goal of minimizing delivery times, reducing energy consumption, and optimizing operational costs [36,50]. The safety of a delivery system, on the other hand, relies on the awareness of terrain specifics, identification of potential obstacles, and assessment of urban density to collectively contribute to the selection of optimal delivery routes. Real-time adaptability is a hallmark of a robust drone delivery system for the dynamic and unpredictable nature of the operational environment [51]. Integrating systems capable of dynamically adjusting routes based on real-time data, such as weather conditions, traffic congestion, and restrictions, ensures flexibility and responsiveness.

3.3.2. Altitude Selection

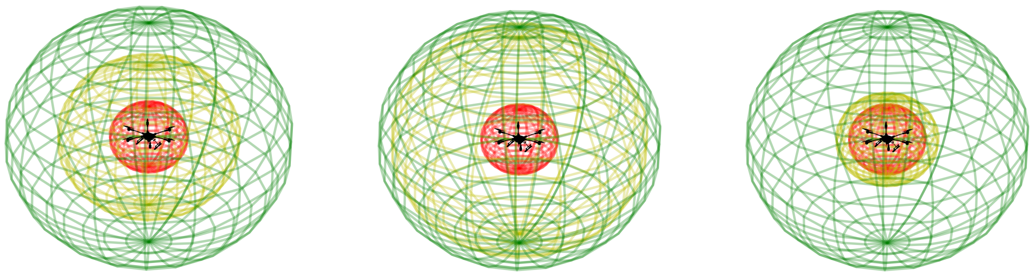
Similar to path selection, selecting the optimal flight altitude becomes a critical decision factor in two-dimensional operations at a specific height. Slicing the third dimension into layers leverages pre-defined horizontal corridors for efficient drone navigation. The selection of the height is influenced by a multitude of environmental and operational parameters, such as meteorological conditions (wind speed, turbulence), dynamic airspace restrictions (temporary closures, flight limitations), and the presence of obstacles (buildings, power lines) [52,53]. To address these complexities, the integration of onboard systems capable of real-time data processing is crucial. Typically, the selected altitude remains unchanged; however, in the presence of environmental influences, adjustments become necessary. This semi-static decision-making approach offers several advantages, including enhanced operational efficiency by enabling on-the-fly adjustments based on real-time data, improved responsiveness to unforeseen obstacles or airspace restrictions, and, ultimately, safer drone operations.

3.4. Safety Challenges

In contrast to the other challenges, security challenges require decisions to be characterized by continuous adaptation. They are constantly re-evaluated and can be modified in response to the ever-changing nature of the environment. Therefore, communication among participants is essential. This iterative process ensures that the chosen course of action remains in line with the current state of the system and its environment. To illustrate the complexities of dynamic decision making in aerial drone operations, the following sections delve into the specific scenarios depicted in Figure 1. These examples show the real-world challenges that drone airlines must face to achieve efficient and safe flight operations.

3.4.1. Safety Zone Definition

All previously defined applications are relatively static since they are not regularly updated based on dynamic parameters such as velocity or network quality. In contrast, the choice of the size of the safety zone is frequently recalculated and determined. The safety zones are presented in Figure 3 and have been conceptualized as a spherical perimeter enveloping the drone's operational core. This spherical design not only represents a crucial structural aspect of the safety measures but also ensures its protected operational space from all directions.



(**a**) Normal flying behavior (**b**) Critical flying behavior (**c**) Safe flying behavior

Figure 3. The safety zones of a drone during flight comprise three levels. The first level A (red) and third level C (green) zones remain constant for simplicity, while the second zone B (orange) is adaptable and varies based on the drone's flying behavior. Note that the schematic representation of the zones has been intentionally sketched at a reduced scale for clarity.

The safety zone of the drone contains three strategic levels, each serving a distinct and integral role in protecting the drone's operation and mitigating collision risks. The first level, A, designated as the emergency zone, assumes essential importance due to its criticality in collision prevention and the preservation of the operational integrity that it should be rigorously avoided and not penetrated under any circumstances. Moving to the second level, B, we encounter the intermediate zone, which demands proactive measures and strategic actions to ensure collision avoidance. The determination of the second zone involves the utilization of diverse dynamic parameters like velocity, quality of communication [54], or environmental conditions (see Figure 3). At the third level, C, termed the secure zone, drones are afforded the latitude to conduct their routine operations without the need for active conflict management. Nonetheless, within this sphere, drones engage in a collaborative information-sharing process. The information-sharing procedure aims to resolve conflicts among drones that disrupt each other's safety zones to prevent collisions by determining priorities.

The concept of a safety zone entails that sphere A must be contained within sphere B, and sphere B must, in turn, be contained within sphere C, expressed as $A \subseteq B \subseteq C :\Longleftrightarrow \forall x \in A : x \in B : x \in C$. The size of each zone (A_r, B_r, C_r) is determined by a set of cascaded functions:

$$C_r = (C_{\text{max}} - C_{\text{min}})C_s + C_{\text{min}} \tag{1}$$
$$B_r = (C_r - B_{\text{min}})B_s + B_{\text{min}} \tag{2}$$
$$A_r = (B_r - A_{\text{min}})A_s + A_{\text{min}} \tag{3}$$

Here, $A_s, B_s, C_s \in [0, 1]$ represents the level of danger in a given situation, subject to the constraint that $A_{\text{min}} < B_{\text{min}} < C_{\text{min}}$. The minimum sizes of the three safety zones $A_{\text{min}}, B_{\text{min}}, C_{\text{min}}$ and the maximum size of the safety zone C_{max} depend on the specific requirements and parameters of the system and must be determined accordingly. These definitions are used to determine the size of the safety zone depending on various parameters and their scaling factors, using minimum and maximum values as reference points. This nested structure provides a clear hierarchy and helps to maintain safety margins while allowing for flexibility within the broader operational area.

3.4.2. Priority Definition

To enhance the efficiency of the drone delivery network, the integration of a robust traffic management system becomes essential. Dynamic rule-based decision-making finds then another practical application in determining the priority of drones in situations where conflicts arise [50,55]. In Figure 4, a scenario unfolds where two drones are illustrated in conflict, with one drone exhibiting high velocity, thereby necessitating a larger safety zone.

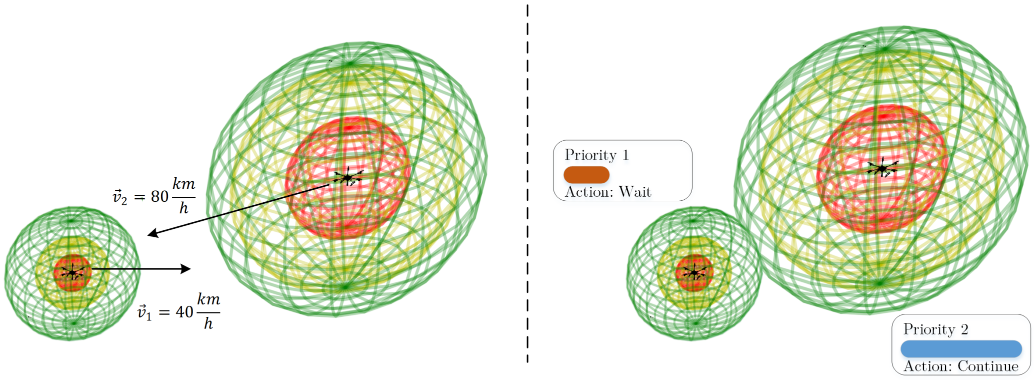


Figure 4. Two drones in a state of conflict, wherein one drone has high velocity, thereby requiring an expanded safety zone. The blue priority is assigned to the faster drone on the right, while the red priority is assigned to the slower drone on the left.

Critical parameters in this context involve the continuous monitoring of each drone's battery level to assess the available energy for ongoing missions. Additionally, considerations extend to factors such as delivery time windows, the nature of the package contents (especially critical for items like medical supplies), and customer preferences, which collectively contribute to the intricate task of prioritizing drone operations [31]. This monitoring mechanism provides real-time insights into the operational dynamics, facilitating prompt decision-making to address challenges and ensure the safe execution of missions. Moreover, user-driven adaptability introduces a dynamic layer to the system. One of the key user-modifiable static parameters is the assigned importance level of the cargo being transported. In essence, priority assignment is essential, as it not only prevents conflicts but also increases the overall efficiency of the drone delivery network.

3.5. Integration and Adaptation

In crafting the framework for the deployment of delivery drones, two key components come to the forefront: system integration and continuous adaptation. The integration of various decisions is the core of a successful drone delivery system. This involves a harmonious combination of various challenges into a unified and efficient system. By aligning these crucial decisions into a unified form, the delivery network transforms into a cohesive entity. This integration not only ensures a seamless flow of operations but also facilitates enhanced coordination between diverse facets, laying the groundwork for a sophisticated and interconnected drone delivery ecosystem. Moreover, due to broad relevance, the implementation within a Docker container ensures the adaptability of the algorithm in different decision-making applications and enables seamless deployment. Beyond the initial integration, continuous adaptation stands as a permanent advancement process. Implementing user-friendly adaptable algorithms allows the system to adjust dynamically to changing conditions. The objective is to iteratively enhance overall system performance over time. This proactive approach ensures that the drone delivery network remains adaptive, efficient, and responsive to evolving challenges and opportunities. By systematically incorporating these steps into the deployment strategy, a robust framework emerges that considers the complexities of different domains and exhibits adaptability and resilience in the face of dynamic operational conditions, providing a foundation for future advancements and optimizations in the realm of autonomous aerial logistics.

4. Rule-Based Scoring Algorithm

In the complex scenario of multimodal drone logistics, assigning scores emerges as a critical focal point for optimizing diverse applications. The selection of a specific drone for a given task is contingent upon a multifaceted set of considerations, ranging from payload characteristics and delivery urgency to real-time environmental variables. Similarly, the essence of effective prioritization lies in the deployment of a sophisticated algorithm designed to make real-time decisions. This algorithm must dynamically consider factors such as the operational status of each drone, aerial traffic conditions, energy constraints, and potential conflicts among multiple participants or environmental obstacles. The decision-making framework serves as the challenge of this logistical ecosystem, applying computational methods to assess and assign scores based on a comprehensive set of parameters.

Within this section, we introduce a prioritization framework adapted for diverse scenarios within a drone logistics environment, particularly addressing conflicting situations. Before delving into the details, we will provide an overview of the challenges inherent in this context and clarify various parameters that influence the decision-making process.

4.1. Problem Definition

In this research paper, we delineate two primary challenges. Firstly, the challenge is to formulate a flexible and easily configurable mathematical model that efficiently translates the complexity of multiple parameters into a unified and adjustable scale, enabling decision-making processes within the designated range. Therefore, consider a fleet of drone airlines that is represented by a collection of k measurements $m \in \mathbb{R}^k$ such as battery life, payload capacity, maximum speed, and operational cost. The task is to determine the function $f : \mathbb{R}^k \to \mathbb{R}$ that assigns a score s based on parameters and expert knowledge. This function should be straightforwardly configured, requiring only logistical knowledge rather than mathematical expertise.

The second problem is to optimize the overall process, including responsiveness to changes, computational overhead, and efficiency in capturing system dynamics. Hence, the challenge is to develop an efficient updating strategy for the function output based on events occurring within the system or the frequency of input changes. With event-based updating, the system responds to specific events or conditions by triggering updates, whereas, with frequency-based updating, the update occurs at fixed time intervals, regardless of events. The event-based approach allows for a more dynamic and resource-efficient update, as it only occurs when needed, such as recalculating priorities when a drone violates the safety zones of another. The frequency-based approach ensures a regular update, regardless of events, i.e., the safety zone size, which depends on the dynamic velocity. Mathematically, the updated output can be represented as

$$s = \begin{cases} f(m), & \text{if } e_i \vee t \pmod{T} = 0 \\ s, & \text{otherwise,} \end{cases} \tag{4}$$

where $E = \{e_1, e_2, \ldots, e_n\}$ represent the set of events triggering updates. The function output s is updated whenever an event e_i in E occurs or is updated periodically every T unit of time t at regular intervals.

4.2. Data Collection and Parameters

In this section, we delineate a comprehensive set of parameters associated with drones, categorizing them into three distinct classes: pre-defined, external, and internal. Pre-defined parameters are established before flight, subject to potential variations based on evolving conditions. For instance, the significance of the cargo may shift from high to low or vice versa during flight, necessitating adjustments in these parameters. External parameters are integral to the overall functioning of the drone but are contingent on environmental conditions, regulations, and operational priorities that may dynamically impact its scores. Conversely, internal parameters pertain to the metrics measured directly by the drone's onboard sensors. These parameters provide real-time data crucial for the drone's autonomous decision-making processes, including navigation, obstacle detection, and performance monitoring. The accuracy and reliability of internal parameters significantly influence the overall operational efficiency and safety of the drone. Table 1 shows the classification of different parameters that form the groundwork for subsequent discussions on optimization strategies.

Table 1. Classification of several drone parameters: categorization into predefined, externally influenced, and sensor-derived internal metrics crucial for the optimization of drone operations.

	Parameter	Domain	Unit	Note
Pre-defined	Payload importance	$\{I \in \mathbb{N} \mid 0 \leq I \leq 100\}$	%	Indicates significance.
	Task complexity	$\{c \in \mathbb{N} \mid 0 \leq c \leq 100\}$	%	Level of difficulty of task.
	Payload sensitivity	$\{s \in \mathbb{N} \mid 0 \leq s \leq 100\}$	%	Susceptibility to external factors.
	Battery life thresholds	$\{b_\theta \in \mathbb{N} \mid 0 \leq b_\theta \leq 100\}$	%	Thresholds for charging.
	Task duration	$\{t_d \in \mathbb{Q} \mid 0 \leq t_d \leq t_{max}\}$	minutes	Time to complete mission.
External	Air traffic density	$\{\rho_a \in \mathbb{Q} \mid 0 \leq \rho_a \leq 1\}$	-	Volume of air traffic.
	Weather conditions	$\{\Omega \in \mathbb{Q} \mid 0 \leq \Omega \leq 1\}$	-	Current atmospheric state.
	Urban density	$\{\rho_u \in \mathbb{Q} \mid 0 \leq \rho_u \leq 1\}$	-	Population concentration.
	Communication SINR	$\{\sigma_R \in \mathbb{Q} \mid 0 \leq \sigma_R \leq 30\}$	dB	Signal-to-noise ratio.
	Communication RSRQ	$\{\sigma_Q \in \mathbb{Q} \mid -19.5 \leq \sigma_Q \leq -3\}$	dB	Reference signal received quality.
	Communication RSRP	$\{\sigma_P \in \mathbb{Q} \mid -140 \leq \sigma_P \leq -44\}$	dB	Reference signal received power.
Internal	Longitude	$\{\lambda_{lon} \in \mathbb{Q} \mid -180 \leq \lambda_{lon} \leq 180\}$	degrees	Precise location data.
	Latitude	$\{\lambda_{lat} \in \mathbb{Q} \mid -90 \leq \lambda_{lat} \leq 90\}$	degrees	Precise location data.
	Height	$\{h \in \mathbb{Q} \mid 0 \leq h \leq h_{max}\}$	m	Height of the drone.
	Obstacle distance	$\{d \in \mathbb{Q} \mid 0 \leq d \leq d_{max}\}$	m	Distance from obstacles.
	Battery life	$\{b \in \mathbb{Q} \mid 0 \leq b \leq 100\}$	%	Remaining battery life.
	Lidar data	$\{d_l \in \mathbb{Q} \mid 0 \leq d_l \leq d_{l,max}\}$	m	Scanning information.
	Flight speed	$\{v \in \mathbb{Q} \mid 0 \leq v \leq v_{max}\}$	$\frac{m}{s}$	Current velocity of drone.

All the parameters listed in the table include the capability for real-time modification throughout a flight. Alongside these dynamic parameters, there exist certain static parameters that remain unaltered throughout the operational phase. Examples of such unchangeable parameters include the weight of the cargo, the maximum payload capacity, or the battery capacity. These static factors serve as foundational elements, contributing to the inherent characteristics and limitations of the drone and setting a structural framework that remains constant during flight operations.

4.3. Scoring Algorithm

The heart of our methodology lies in the mathematical framework used to calculate numerical scoring values for each drone. This calculation is based on the fuzzy logic assessment and the combination of dynamic and semi-static parameters. Fuzzy sets and rules are designed to handle imprecise data and transform them into meaningful membership values. Figure 5 shows the main steps for the inference process of decision-making.

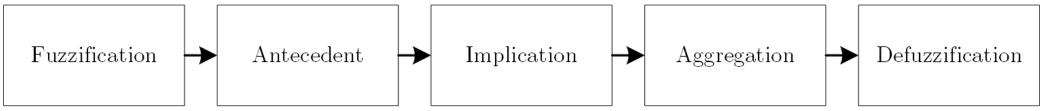


Figure 5. Fuzzy logic framework for score calculation using multiple parameters [56].

The mathematical representation of this scoring inference process can be described as follows:

$$\zeta = D(\Gamma(I(T(\mu_A(x), \mu_B(y)), \mu_C(z)))). \tag{5}$$

This function is our objective within Section 4.1 and, in the following subsection, we provide a detailed breakdown of the steps employed in the decision-making framework. We will present the mathematical approaches for calculating a score that allows for critical choices. By delving into this mathematical framework, we aim to provide a comprehensive understanding of the intricate logic that empowers the system to make real-time, data-driven decisions. The comprehensive inference process is subsequently demonstrated in the experiments in Section 5, clarifying the impact of each step by the analysis of two distinct applications.

4.3.1. Fuzzification

Fuzzification is the process of converting crisp data, characterized by precise values, into fuzzy data, where values possess degrees of membership to various fuzzy sets. This mathematical transformation is formally defined by the notation $A = \{\mu | f : X \to [0,1]\}$ that defines a fuzzy set A, where μ represents a membership function. This function operates on elements x and maps them to the range $[0,1]$. The resulting value, denoted by $\mu_{A,i}(x) \in [0,1]$, indicates the degree of membership of element x in the function i of the fuzzy set A. Higher values closer to 1 represent a stronger membership while values closer to 0 indicate a weaker membership. These functions must satisfy the following properties:

1. Non-negativity: $\mu(x) \geq 0 \quad \forall\, x \in X$;
2. Range: $0 \leq \mu(x) \leq 1 \quad \forall\, x \in X$;
3. Continuity: $\mu(x)$ is continuous $\forall\, x \in X$.

Table 2 showcases several examples of membership functions that meet the desired characteristics. The functions in the table use x to represent the variable, and the remaining parameters primarily control the function's center and width.

Table 2. Examples of fuzzy membership functions. The functions utilize the variable x to denote the input, while the remaining parameters primarily control the function's center and width [57].

Function	Definition
Sigmoid	$\mu(x; a, c) = \frac{1}{1+e^{-a(x-c)}}$
Gaussian	$\mu(x; \sigma, c) = e^{\frac{-(x-c)^2}{2\sigma^2}}$
Linear	$\mu(x; a, b) = \max(\min(\frac{x-a}{b-a}, 1), 0)$
Triangular	$\mu(x; a, b, c) = \max(\min(\frac{x-a}{b-a}, \frac{c-x}{c-b}), 0)$
Trapezoidal	$\mu(x; a, b, c, d) = \max(\min(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}), 0)$

Following the fuzzification of input values, where crisp data are transformed into membership degrees of fuzzy sets, fuzzy rules are applied to derive a decision. These rules function as a collection of conditional statements that operate on the fuzzified inputs to determine an appropriate output. Each fuzzy rule typically follows a well-defined structure, i.e., *If x in $\mu_{A,i}$ AND y in $\mu_{B,j}$ THEN z in $\mu_{C,k}$*. In this example, the antecedent utilizes the combination of fuzzified inputs $\mu_{A,i}(x)$ and $\mu_{B,j}(y)$ based on the operator AND, where A and B define the fuzzy sets of the input variables and i, j the specific membership function of the rule. The consequent specifies the resultant fuzzy membership function $\mu_{C,k}(z)$

for the output variable. In the following sections, we describe the rule operators and the implication process.

4.3.2. Antecedent

In fuzzy logic, several operators play a crucial role in manipulating fuzzy sets and constructing fuzzy rules. There are three main operators: AND, OR, and NOT. These operators enable the handling of uncertain and imprecise information by allowing for flexible reasoning and decision-making. They form the backbone of fuzzy logic systems, facilitating the representation and manipulation of fuzzy sets.

A *t*-norm (triangular norm) in fuzzy logic mathematically defines how the degree of membership of two fuzzy sets is combined, representing a fuzzy AND operation. There is not a single universal definition for a *t*-norm, but instead, a set of properties where any function satisfying these properties can be considered as a *t*-norm:

1. Commutativity: $T(\mu_{A,i}(x), \mu_{B,j}(y)) = T(\mu_{B,j}(y), \mu_{A,i}(x))$.
2. Monotonicity: $\mu_{A,i}(x_1) \leq \mu_{A,i}(x_2) \wedge \mu_{B,j}(y_1) \leq \mu_{B,j}(y_2) \rightarrow$ $T(\mu_{A,i}(x_1), \mu_{B,j}(y_1)) \leq T(\mu_{A,i}(x_2), \mu_{B,j}(y_2)) \; \forall \; x, y$.
3. Boundary Condition: $T(1,1) = 1 \wedge T(0, \mu_{B,j}(y)) = T(\mu_{A,i}(x), 0) = 0 \; \forall \; x, y$.

The most frequently encountered *t*-norms under the premise "If x in $\mu_{A,i}(x)$ AND y in $\mu_{B,j}(x)$" are evaluated as follows:

$$T(\mu_{A,i}(x), \mu_{B,j}(y)) = \begin{cases} \min(\mu_{A,i}(x), \mu_{B,j}(y)) & \text{if min} \\ \mu_{A,i}(x) \cdot \mu_{B,j}(y) & \text{if product} \end{cases} \tag{6}$$

If the minimum *t*-norm is used, the premise would be evaluated as $\min(\mu_{A,i}(x), \mu_{B,j}(y))$. This intuitive operator reflects the most restrictive interpretation of AND. If either element has a weak membership, the combined membership will also be weak. This reflects a strict AND condition, where both elements need strong membership for the combined result to be strong. If the product *t*-norm is used, the premise would be evaluated as $\mu_{A,i}(x) \cdot \mu_{B,j}(y)$. This operator offers a stricter intersection compared to the minimum *t*-norm. A lower membership degree in either set significantly reduces the combined membership due to multiplication.

Similarly to the *t*-norm, there is not a single universal definition for an *s*-norm representing the complementary *t*-norm and fuzzy OR operation. Any function satisfying the following properties can be considered as an *s*-norm.

1. Commutativity: $S(\mu_{A,i}(x), \mu_{B,j}(y)) = S(\mu_{B,j}(y), \mu_{A,i}(x))$.
2. Monotonicity: $\mu_{A,i}(x_1) \leq \mu_{A,i}(x_2) \wedge \mu_{B,j}(y_1) \leq \mu_{B,j}(y_2) \rightarrow$ $S(\mu_{A,i}(x_1), \mu_{B,j}(y_1)) \leq S(\mu_{A,i}(x_2), \mu_{B,j}(y_2)) \; \forall \; x, y$.
3. Boundary Condition: $S(0,0) = 0 \wedge S(1, \mu_{B,j}(y)) = S(\mu_{A,i}(x), 1) = 1 \; \forall x, y$.

The most frequently encountered *s*-norms under the premise "If x is $\mu_{A,i}(x)$ OR y is $\mu_{B,j}(x)$" are evaluated as follows:

$$S(\mu_{A,i}(x), \mu_{B,j}(y)) = \begin{cases} \max(\mu_{A,i}(x), \mu_{B,j}(y)) & \text{if max} \\ \mu_{A,i}(x) + \mu_{B,j}(y) - \mu_{A,i}(x) \cdot \mu_{B,j}(y) & \text{if probabilistic sum} \end{cases} \tag{7}$$

The max *s*-norm is the most straightforward interpretation of "OR". If either element has a strong membership (high degree), the combined membership will also be strong. The product sum offers a compromise between the maximum *s*-norm and the algebraic sum. It considers both the individual membership degrees and their product.

Antecedents can also be negated using the NOT operator, where the operation is evaluated as follows:

$$N(\mu_{A,i}(x)) = \begin{cases} 1 - \mu_{A,i}(x) & \text{if standard negation} \\ 1 - (\mu_{A,i}(x))^n & \text{if strong negation} \end{cases} \tag{8}$$

The parameter n controls the strength of the negation. Higher values of n lead to a steeper curve and a more pronounced contrast between membership and non-membership. The steeper curve can lead to a loss of information for elements with intermediate membership degrees between 0 and close to 1. These might be compressed into a narrow range near 0, potentially reducing the sensitivity of the system. Conversely, if $n = 1$, standard negation is applied. The curve is linear, providing a gradual decrease in membership degree.

The fuzzy rule evaluation process combines the membership degrees of the rule's antecedents (conditions) using a fuzzy operator (e.g., AND, OR). This resulting value represents the degree of truth for the entire premise (combined conditions) of the fuzzy rule. This degree of truth then becomes crucial in the subsequent step of the inference process, the implication. In the following sections, we consider $T(\mu_{A,i}(x), \mu_{B,j}(y))$ as the antecedent output.

4.3.3. Implication

In this step, the consequence of the rule is made. Here, an implication rule is applied to the membership degrees obtained in the previous step. The implication I is carried out using an implication operator. Several implication operators can be used, but two of the most common are the Mamdani operator and the Larsen operator. The Mamdani operator uses the minimum and the Larsen operator uses the product of the antecedent output $T(\mu_{A,i}(x), \mu_{B,j}(y))$ and the fuzzy output membership function $\mu_{C,k}(z)$:

$$\hat{\mu}_{C,k}(z) = \begin{cases} \min(T(\mu_{A,i}(x), \mu_{B,j}(y)), \mu_{C,k}(z)) & \text{if Mamdani} \\ T(\mu_{A,i}(x), \mu_{B,j}(y)) \cdot \mu_{C,k}(z) & \text{if Larsen} \end{cases} \tag{9}$$

In the implication step, each fuzzy rule's consequent function is evaluated based on the degree of matching. These modified consequent membership functions $\hat{\mu}_{C,k}(z)$ represent the partial outputs of the fuzzy system in response to the given inputs. Combining these partial outputs from all activated fuzzy rules results in an overall output fuzzy set, which is the next step of the inference process.

4.3.4. Aggregation

The aggregation function Γ plays a critical role in fuzzy logic systems by combining the fuzzy membership functions $\hat{\mu}_{C,k}(z) \in \mathbb{R}^{N_\mu}$ from all activated K rules into a single fuzzy function.

$$\Gamma : \mathbb{R}^{N_\mu \times K} \to \mathbb{R}^{N_\mu} \tag{10}$$

Examples of aggregation functions include maximum (union), average, and sum. The output function μ_ψ serves as the basis for decision-making within the system. Crucially, aggregation incorporates a weight w associated with each rule k, determining the overall contribution of each rule to the final aggregated output. Any aggregation function should fulfill the following property:

1. Commutativity: $\Gamma(\hat{\mu}_{C,1}(z), \hat{\mu}_{C,2}(z)) = \Gamma(\hat{\mu}_{C,2}(z), \hat{\mu}_{C,1}(z))$.

Once the fuzzy sets obtained from the implication are aggregated, the resulting fuzzy set represents the combined fuzzy logic system's activation level.

$$\mu_\psi = \Gamma(I(T(\mu_{A,i}(x), \mu_{B,j}(y)), \mu_{C,k}(z)), w_k) \tag{11}$$

However, to obtain a crisp output from the fuzzy inference process, we need to convert this fuzzy set into a single numerical value.

4.3.5. Defuzzification

Defuzzification serves as the final stage within a fuzzy logic system. Here, the system transforms the fuzzy output set, characterized by its membership function, into a single, crisp (numerical) output value.

$$D : \mathbb{R}^{N_\mu} \to \mathbb{R} \tag{12}$$

This crisp output facilitates decision-making or control actions within the system. Various defuzzification methods exist, such as the centroid, mean-of-maximum (MOM), and center-of-area (COA) methods, each with its advantages and limitations. These functions are presented along with their definitions in Table 3.

Table 3. Examples of defuzzification functions that determine the crisp output ζ.

Function	Definition
Centroid	$\zeta = \dfrac{\int z \cdot \mu_\psi(z)dz}{\int \mu_\psi(z)dz}$
Mean-of-Maximum	$\zeta = \frac{1}{\lvert z^* \rvert} \sum z^*$ with $z^* \in \arg\max_z \mu_\psi(z)$
Center-of-Area	$\int_0^{z^*} \mu_\psi(z)dz = \int_{z^*}^{\infty} \mu_\psi(z)dz$

The selection of a suitable defuzzification method depends on the specific application and the desired interpretation of the crisp output. The centroid method provides a well-balanced representation of the fuzzy output set, considering both the membership degrees and the potential output values. MOM offers a simpler approach but might be sensitive to outliers in the membership function. COA focuses on the area under the membership function curve. In conclusion, defuzzification bridges the gap between the fuzzy domain of the output set and the crisp domain of decision-making within fuzzy logic systems. At this stage, the mathematical inference process ends, since the output of the defuzzification serves as the decision.

4.4. Operation and Implementation

The framework for calculating scores of multiple parameters within a specific application introduces a universal and efficient solution, designed to enhance adaptability and ease of deployment. This framework leverages a configuration, allowing users to tailor the system to the unique requirements of their application. By encapsulating this solution within a Docker container, we ensure a seamless and portable deployment, transforming it into a general-purpose tool suitable for diverse environments. The core functionality of the framework is implemented using Python, offering a flexible and widely adopted programming language for data analysis and computational tasks. Through the utilization of scoring principles, the framework accommodates the inherent uncertainty and imprecision present in real-world applications, providing a robust mechanism for scoring. The configuration serves as the backbone of the framework, enabling users to specify the parameter sets, rules, and functions governing the scoring process. Upon initiation of the process, the code systematically loads the configuration, dynamically constructing all essential functions and memberships as specified. Figure 6 provides a visual representation, showcasing each composed element derived from the multitude of options available within the system.

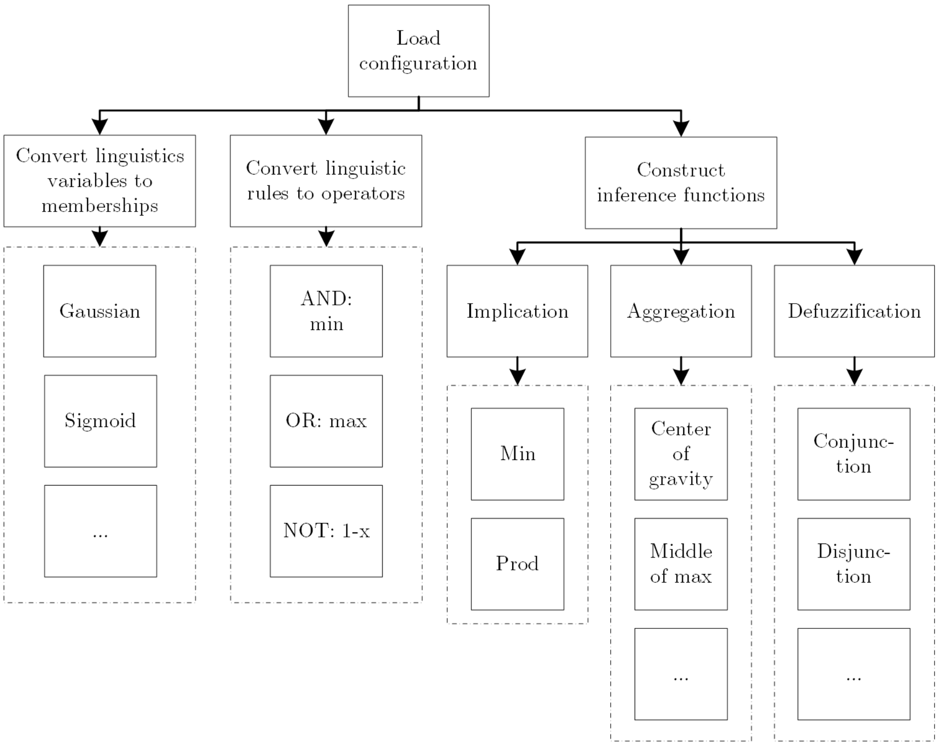


Figure 6. Constructing the scoring algorithm based on the configuration that serves as the fundamental element for decision making.

As outlined in Figure 1, decisions can be broadly categorized into static, semi-static, and dynamic types. Static decisions are finalized and remain unchanged, while dynamic decisions involve continuous score calculations. Implementing this involves an iteration, where dynamic parameters are measured, and the scoring algorithm is applied frequently. For semi-static decisions, a system refresh can be triggered using an event. Therefore, we propose two possibilities for triggering the algorithm: frequency-based and event-based. Moreover, in examples where a decision is dynamically configured as its parameters change, the use of lookup tables can significantly optimize computational efficiency. Consider, for example, the safety zone, which is configured initially and updated based on parameters. In such cases, consulting a pre-established lookup table proves more efficient than recalculating the overall score repetitively, accelerating the decision-making process.

4.5. Composition and Flowchart

Efficient and safe drone airline logistics demand navigating a dynamic web of decision-making processes. The flowchart in Figure 7 serves as a roadmap, outlining the key factors considering the decisions of Figure 1. It is crucial to recognize the interconnected nature of these decisions, where each step influences and depends on others, creating a cascading effect throughout the planning process. This flowchart provides a simplified overview of the intricate decision-making processes involved in drone airline logistics. By considering a multitude of parameters and their interconnected nature, drone operators can ensure efficient, safe, and adaptable flight operations within the ever-changing operational environment.

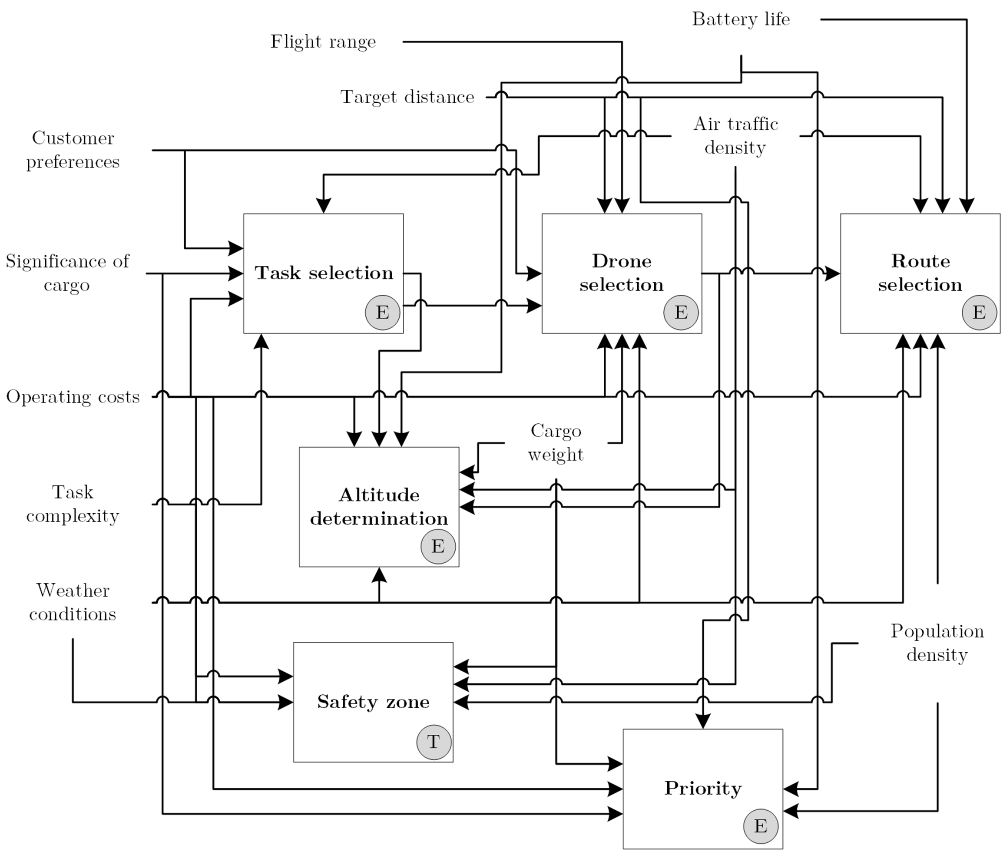


Figure 7. This flowchart depicts various decision-making processes. The boxes represent the decision-making steps, and the inputs and outputs represent the parameters. The circles inside the boxes indicate whether the decision is event-based (E) or time/frequency-based (T).

Event-based and frequency-based approaches are crucial and play significant roles in data processing. While both strategies aim to make relevant decisions from data streams, they utilize different access methods. To trigger the algorithm by events, several types are available:

1. System Events: These events are triggered by internal system activities.
2. Sensor Events: These events originate from sensors that detect changes in the environment.
3. Business Events: These events represent significant occurrences within a business process.
4. External Events: These events originate from outside the system and can have an impact on its operations.

The selection between event-based and frequency-based approaches hinges on various factors, including the nature of the data, application requirements, and available resources. In some cases, both approaches might be necessary to fulfill an application's needs. For instance, an application could leverage event-based methods for high-priority events and frequency-based methods for retrieving less time-sensitive data.

5. Experiments

In this section, we conduct a comprehensive assessment of the effectiveness of our proposed methodology in addressing the dynamic safety zone definition, drone priority, and route selection. Before diving into the decision-making process, we introduce first the baseline and data preprocessing. Subsequently, we expound upon the specifics of our experimental setup for the static and dynamic parameters over the complete inference process. This in-depth analysis allows us to gain insights into the performance and effectiveness of the fuzzy-logic-based scoring algorithm in handling the intricate task of decision-making in drone logistics.

5.1. Baseline

To the best of our understanding, we have been unable to find a comparable general decision-making system. In order to assess the effectiveness of the fuzzy-based scoring system, it is necessary to evaluate the downstream tasks that occur subsequent to the decision-making process. As a result, we are comparing this approach with a similar rule-based structured Boolean decision-making system that operates on the same rules, thus ensuring comparability with respect to the input parameters. Boolean decision-making is described by

$$\zeta = \frac{1}{N}\sum_{n=1}^{N} \max_{i=1}^{I} T(\mu_{A,i}(x), \mu_{B,i}(y)) \to g_i(z_n). \tag{13}$$

Here, the operators T are now Boolean connectives, and the functions μ are rectangular functions, also referred to as the rect function, which is defined as

$$\operatorname{rect}\left(\frac{x}{a}\right) = \Pi\left(\frac{x}{a}\right) = \begin{cases} 0, & \text{if } |x| > \frac{a}{2} \\ \frac{1}{2}, & \text{if } |x| = \frac{a}{2} \\ 1, & \text{if } |x| < \frac{a}{2} \end{cases} \tag{14}$$

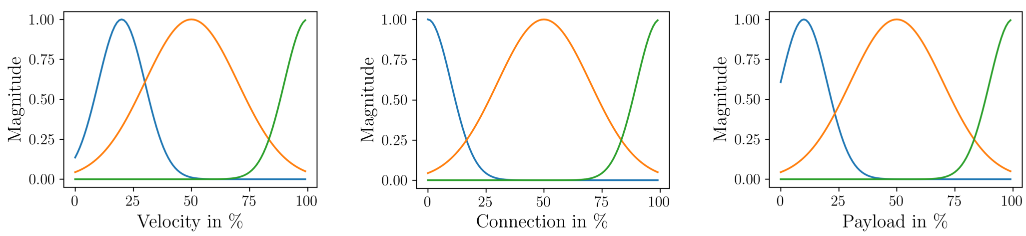
This comparison allows us to measure the performance and effectiveness of the system in relation to the Boolean decision-making approaches.

5.2. Data Preprocessing

The dynamic parameters are collected through a network of sensors strategically positioned to monitor various aspects of the drone's environment. To facilitate comfortable use and interpretation for end-users, the collected data undergo a normalization stage, wherein the collected data are transformed into a standardized range, typically scaled between 0 and 100. Normalization simplifies data interpretation and user interactions by bringing all sensor readings into a uniform and easily comprehensible format. The transformed data becomes a valuable input for the decision-making processes, allowing for more robust and efficient management.

5.3. Inference Process: Safety Zone

The selection of the safety zone of a drone during flight is imperative since violation of the zone must lead to preventive actions. Therefore, we select the parameters of velocity, quality of connection, and payload weight. We use three Gaussian membership functions to define each input parameter, as shown in Figure 8.



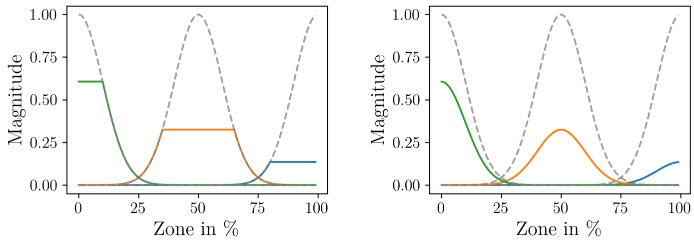
(**a**) Parameter velocity (**b**) Parameter connection (**c**) Parameter payload

Figure 8. The membership functions for the three parameters are depicted: velocity, connection, and payload. The membership function in blue represents the correspondence to the linguistic variable low, orange the correspondence to mid, and green the correspondence to high.

The speed at which the drone is operating influences its maneuverability and response time. Higher velocities may require a larger safety zone to accommodate sudden changes in direction. The reliability of communication links between the drones and the ground station also plays an important role in the safety zone size. The weight of the payload being carried by the drone is a static parameter. Heavier payloads may influence the drone's performance and safety requirements, necessitating adjustments to the safety zone. Fuzzy rules allow us to incorporate vagueness and degrees of truth, making them suited for situations with concepts like "high", "mid", or "low". Here, the rules are defined as follows:

1. If the velocity is high or connection is low or payload is high, then the zone is high.
2. If the velocity is mid and connection is mid and payload is mid, then the zone is mid
3. If the velocity is low or connection is high or payload is low, then the zone is low.

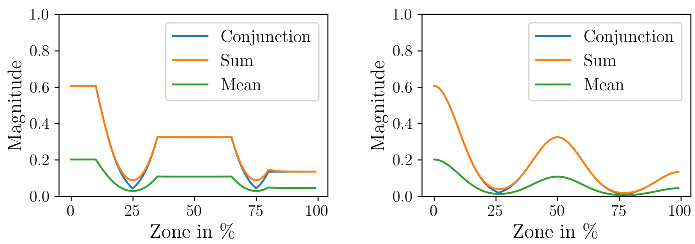
Upon applying the prescribed rules, the consequence of the implication is typically a degree of membership that represents the strength of the relationship between input and output variables. Similar to the input, the output variable is depicted as a fuzzy set utilizing Gaussian functions. Figure 9 shows two different implication methods and their influence on the output based on the rules and the input.



(**a**) Method minimum (**b**) Method product

Figure 9. The influence (green, orange, and blue) of applying two different implication methods on the output fuzzy set (dashed).

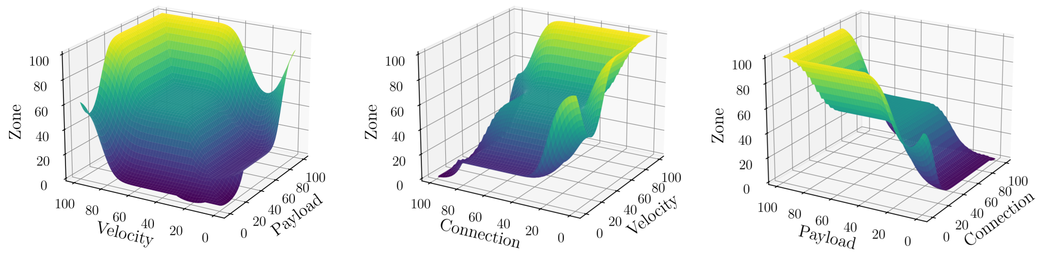
Aggregation is a pivotal component in synthesizing complex data relationships. Fuzzy aggregation serves as a mechanism for consolidating diverse sources of information, allowing for a comprehensive analysis of the observed data. Figure 10 presents three different aggregation methods on the two different consequences of Figure 9.



(**a**) Implication with minimum (**b**) Implication with product

Figure 10. The aggregation of the resulting membership function of the implication into one membership function using three different methods.

Fuzzy defuzzification operates as the bridge between fuzzy sets and precise numerical values, enabling us to translate fuzzy outputs into concrete, interpretable results. By employing the center of gravity defuzzification method, the overall fuzzy inference process is completed. Figure 11 is the overall evaluation of the safety zone in a surface presented under the condition that two of the three input parameters are variable while the third input parameter is maintained at a constant value of 50%.



(**a**) Constant connection of 50% (**b**) Constant payload of 50% (**c**) Constant velocity of 50%

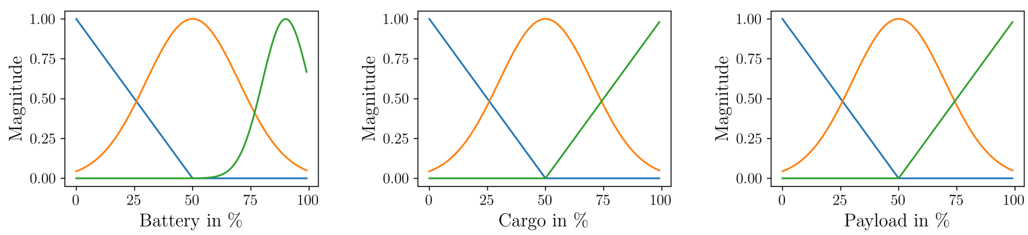
Figure 11. Evaluation of the safety zone scoring depending on different parameters using the product method for implication, conjunction method for aggregation, and center of gravity method for defuzzification.

5.4. Inference Process: Priority

Determining the priority of the drone during conflicting situations is crucial since it directly impacts the safety, efficiency, and success of the mission. This prioritization relies on a variety of factors, including battery level, importance of cargo, and payload weight. Without clear prioritization mechanisms, decision-making in conflicting situations could be chaotic and result in suboptimal or even dangerous outcomes. Therefore, establishing robust frameworks for prioritizing drone actions is essential for ensuring efficient and responsible operation in diverse environments. By evaluating the battery level, cargo significance, and payload weight, the drone's decision-making process becomes more advanced and adaptive. Through the utilization of membership functions, each parameter's influence on the drone's priority can be quantified. We use three membership functions in Figure 12 to define each input parameter. Again, we prefer the Gaussian membership since the Gaussian function provides smoother transitions between linguistic terms, enabling a more precise modeling of uncertainty. Additionally, it is more flexible and can better adapt to different distributions as it is characterized by the parameters mean and standard deviation.

The remaining battery life of the drone is dynamic and can impact its availability for missions. Lower battery levels may influence priority to ensure timely return or recharging. The static importance or significance of the cargo being transported is a parameter set by the user or defined by the nature of the payload. Critical or high-value cargo may receive higher priority. The payload weight that the drone carries represents a fixed parameter. Heavier payloads significantly affect the drone's battery level, demanding faster delivery and elevating the priority of such missions. The rules are straightforward:

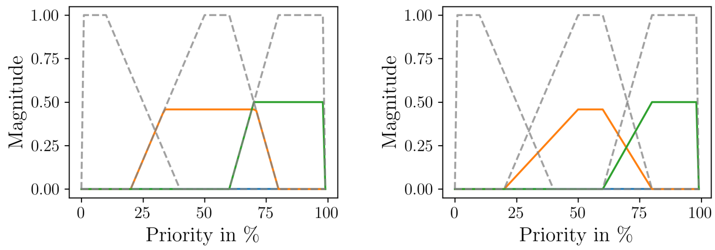
1. If the battery is low or importance is high or payload is high, then the priority is high.
2. If the battery is mid and importance is mid and payload is mid, then the priority is mid.
3. If the battery is high or importance is low or payload is low, then the priority is low.



(**a**) Parameter battery level (**b**) Parameter cargo importance (**c**) Parameter payload

Figure 12. The membership functions for the three parameters: battery, importance, and payload. The membership function in blue represents the correspondence to the linguistic variable low, orange the correspondence to mid, and green the correspondence to high.

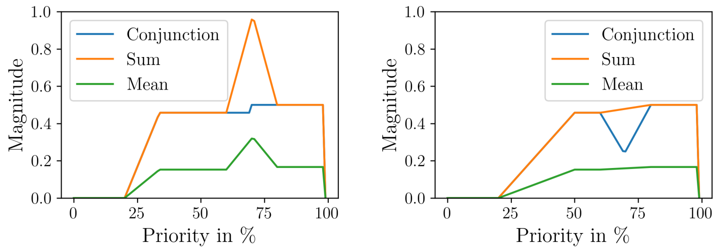
The consequence of the different implication methods and their influence on the output based on the rules is shown in Figure 13. In this example, trapezoidal membership functions are employed for the output fuzzy set.



(**a**) Method minimum (**b**) Method product

Figure 13. The impact (green, orange, and blue) of utilizing two implication methods on the output fuzzy set (dashed).

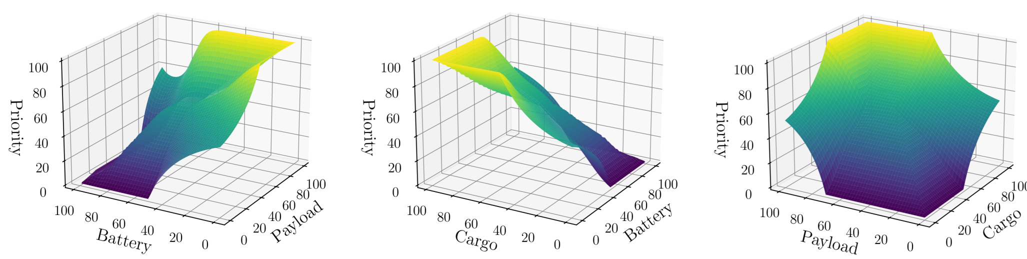
The result of the aggregation of all consequences from the rules using different methods is represented in Figure 14.



(**a**) Implication with minimum (**b**) Implication with product

Figure 14. Combining the resulting membership function of the implication into a single membership function using three different methods.

Using the center of gravity defuzzification method concludes the entire fuzzy inference process. The priority is evaluated on a surface in Figure 15, considering two of the three input parameters as variables while the third input parameter remains constant at 50%.

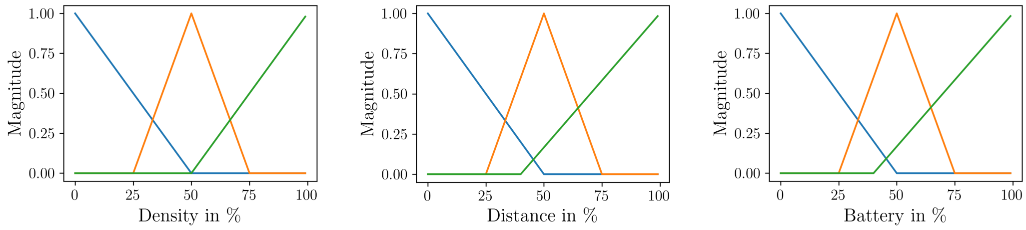


(**a**) Constant importance of 50% (**b**) Constant payload of 50% (**c**) Constant battery of 50%

Figure 15. Evaluation of the priorities depending on different parameters using the product method for implication, conjunction method for aggregation, and center of gravity method for defuzzification.

5.5. Inference Process: Route Scoring

Determining the optimal route among several alternatives is pivotal as certain deliveries prioritize speed while others prioritize safety. Hence, establishing robust frameworks for assessing different routes to select the most suitable one is imperative for ensuring efficient and responsible operation across diverse environments. The evaluation of multiple routes relies on various factors, including battery level, population density, and target distance. By considering the three (or more) parameters, the drone's decision-making process becomes more sophisticated and adaptable. Through the utilization of membership functions, the influence of each parameter on route evaluation can be quantified. We employ three membership functions in Figure 16 to characterize each input parameter. Triangular and trapezoidal membership functions are chosen due to their robustness in handling uncertainties and noise in the data. Their broad, flat tops (in the case of trapezoidal functions) or sharp peaks (in the case of triangular functions) can help to mitigate the effects of minor fluctuations or inaccuracies in the input data. Moreover, their straightforward mathematical expressions render them suitable for practical applications where efficiency and simplicity are important considerations.



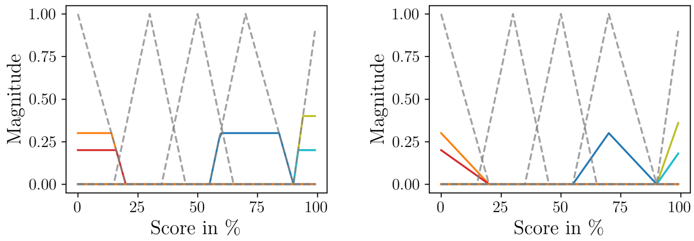
(**a**) Parameter density (**b**) Parameter distance (**c**) Parameter battery

Figure 16. The membership functions for the three parameters: density, distance, and battery. The membership function in blue represents the correspondence to the linguistic variable low, orange the correspondence to mid, and green the correspondence to high.

The drone's remaining battery life is dynamic and can affect its availability for missions. Decreased battery levels directly influence route selection, necessitating shorter routes. Population density also plays a critical role in ensuring safety; typically, drones avoid flying over densely populated areas and decide on alternative routes. The length of the route is linked to efficiency and operational expenses. Longer routes have a substantial impact on the drone's battery level, necessitating quicker deliveries. To create more detailed decision making considering these relations, we define five membership functions for the output set: low, low mid, mid, high mid, and high. The rules are clear and straightforward:

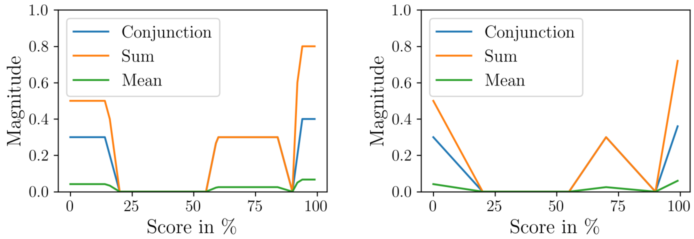
1. If the battery is low and distance is high, then the score is low.
2. If the battery is mid and distance is high, then the score is low mid.
3. If the battery is low and distance is low, then the score is high.
4. If the battery is mid and distance is low, then the score is high mid.
5. if density is high and distance is low, then the score is low.
6. If the battery is high and distance is low and density is high, then the score is low.
7. If the battery is mid and distance is mid and density is mid, then the score is high.
8. If the battery is low and distance is mid and density is mid, then the score is low.
9. If the battery is low and distance is low and density is high, then the score is high.
10. If the battery is high and distance is high and density is low, then the score is high mid.
11. If the battery is high and distance is mid and density is mid, then the score is low mid.

Figure 17 illustrates how various implication methods impact the output based on predefined rules. The piecewise linear nature of membership functions enhances the intuitive understanding of the implication process. After implication, the outcome of aggregating consequences from rules using three different methods is depicted in Figure 18. Employing the center of gravity defuzzification method, the score surface results are shown in Figure 19, where two input parameters vary while the third remains fixed at 50%.



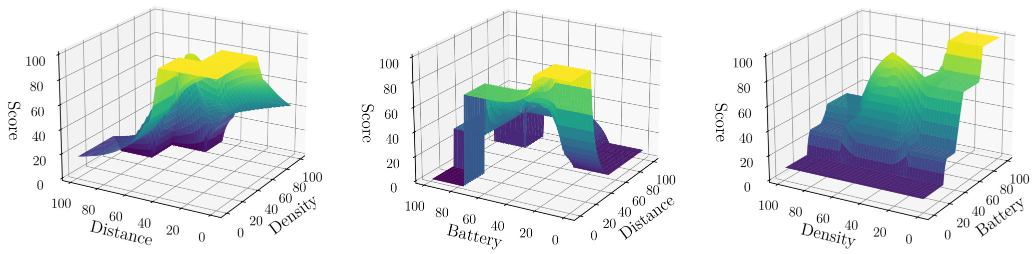
(**a**) Method minimum (**b**) Method product

Figure 17. The influence of using two implication methods is represented by distinct colors, each corresponding to one membership on the original output fuzzy set (dashed).



(**a**) Implication with minimum (**b**) Implication with product

Figure 18. The consolidation of the resulting membership function from the implication into a single membership function using three distinct methods.



(**a**) Constant battery of 50% (**b**) Constant density of 50% (**c**) Constant distance of 50%

Figure 19. Evaluation of the route selection scoring depending on different parameters using the product method for implication, conjunction method for aggregation, and center of gravity method for defuzzification.

5.6. Evaluation

In this section, we will discuss the experimental evaluation of the decision-making algorithm proposed earlier. We will be presenting various example scenarios to address the safety zone, priority, and route selection. Through this evaluation, we will draw conclusions about its suitability for different applications.

5.6.1. Evaluation: Safety Zone and Priority

This evaluation section is dedicated to evaluating the effectiveness and reliability of drones in conflict scenarios, employing prioritization within the defined framework. Initially, we introduce a scenario involving drones facing a conflict situation, wherein we delve into the concepts of safety zones and priorities. It is crucial to note that our focus lies on decision-making rather than path planning for collision avoidance algorithms. Figure 20 shows the scenario in which two drones are following trajectories that present a point of conflict. Drone one follows the red path and drone two follows the blue path. At instant t_1, the parameters reveal that drone one has a smaller safety zone compared to drone two. At t_2, the safety zones of the two drones are colliding; at this time, the drones start to exchange information. At t_3, drone one, which has lower priority, stops. Due to its speed of zero, its safety zone is reduced. Finally, at t_4, the conflict is solved and the drones proceed on their paths. The respective parameters and calculations of the priority and safe zones of each drone at different time instants are specified in Table 4.

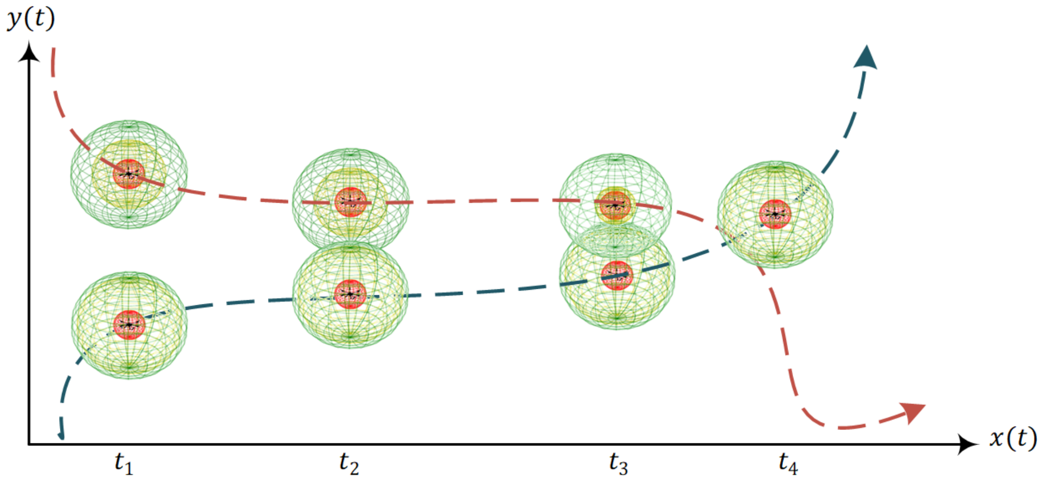


Figure 20. A drone conflict scenario depicted in 2D, illustrating varying sizes of safety zones. The path marked in red corresponds to drone 1, while the one in blue corresponds to drone 2.

Table 4. Evaluation of the conflicting scenario using the safety zone and the priority calculated by fuzzy-logic-based decision making. Here, five parameters are used: connection quality, velocity, battery level, importance of cargo, and payload.

Time	Drone	Parameter Values					Scores	
		Conn.	**Velocity**	**Payload**	**Battery**	**Cargo**	**Zone**	**Priority**
t_1	Drone 1	18.864	58.242	38.026	81.661	50.00	57.545	30.508
	Drone 2	10.074	57.242	89.755	57.102	90.00	74.129	74.821
t_2	Drone 1	16.634	56.312	38.026	76.121	50.00	61.223	38.275
	Drone 2	17.139	58.560	89.755	52.672	90.00	73.88	75.056
t_3	Drone 1	29.023	0.000	38.026	71.837	50.00	31.302	42.981
	Drone 2	29.023	58.352	89.755	47.550	90.00	73.877	75.111
t_4	Drone 1	18.023	59.739	38.026	66.503	50.00	58.867	44.178
	Drone 2	17.189	58.691	89.755	42.312	90.00	73.881	75.118

According to the data in Table 4, we consider a fluctuating communication quality ranging from 10% to 30%. The velocities of both drones remain similar and relatively stable during time intervals t_1, t_2, and t_4, although variations may arise due to external factors such as wind or internal factors like sensor inaccuracies. In the time interval t_3, drone one's velocity drops to zero. This occurrence stems from the comparison across conflicting times of priority scores between drone one (ranging from 38.275% to 42.981%) and drone two (ranging from 75.056% to 75.111%). Consequently, drone one's reduced velocity leads to a decrease in its safety zones, reaching its lowest score at 31.302%. Over time, both drones experience a decline in battery levels, with drone one dropping from 81.661% to 66.503% and drone two from 57.102% to 42.312%, which impacts the drones' priority levels. The significance of cargo and payload remains consistent throughout the drone's journey.

After evaluating this scenario, we conduct a comparison between the fuzzy-logic-based scoring approach and the baseline by exploring various situations that highlight potential challenges. To achieve this, we select scenarios in Table 5 where the parameters defining the priority are both similar and strongly different. Through this meticulous evaluation process, we demonstrate that the fuzzy approach consistently outperforms the baseline, providing valuable insights into the strengths and weaknesses of drone operations in diverse conflict situations. We select parameter samples randomly from a Gaussian distribution with mean 0 and standard deviation 1 ($\mathcal{N}(0,1)$) and then scale these values by a factor of 100. The resulting priorities for both approaches are outlined in Table 5.

Table 5. Evaluation of the priority using the baseline and fuzzy logic scoring algorithm (FLSA) with normalized input parameters. Here, three parameters are used: battery level, importance of cargo, and payload. First, we compare the behavior of prioritization with similar parameter values and then with strongly different parameters.

Index	Similar Parameter Values			Scores	
	Battery	Importance	Payload	Baseline	FLSA
1	28.622	73.720	82.345	83.667	59.799
	23.622	73.720	82.345	83.667	65.499
2	38.237	64.273	48.379	51.905	51.629
	38.237	59.273	48.379	51.905	51.725
3	51.601	22.634	19.328	14.279	50.686
	51.601	22.634	14.328	14.279	50.427
Index	**Diverse Parameter Values**			**Scores**	
	Battery	**Importance**	**Payload**	**Baseline**	**FLSA**
4	18.622	58.622	96.498	83.667	65.854
	48.622	58.622	96.498	0.0	50.291
5	80.238	54.273	16.723	14.279	48.528
	80.238	84.273	16.723	14.279	50.533
6	94.494	36.767	9.328	14.279	31.976
	94.494	36.767	39.328	51.905	47.239

In the upper section of Table 5, we compare the scoring responses of the two approaches, employing similar values across all three cases for comparison. Notably, the baseline yields identical scores and, consequently, identical priorities across these cases, which fails to address the nuanced complexities of conflict resolution. In these cases, additional decision-making is required by employing a random selection, prioritization rule (based on: ID, distance, battery, load, or direction), or central control unit decision. Conversely, the proposed method assigns slightly varied priorities in each case, as the score surface exhibits gradients throughout, minimizing the occurrence of identical numerical values. In contrast, if binary decision-making is used, the system loses degrees of freedom. This means that each input is assigned exactly to a specific category without allowing fuzzy transitions between the categories. As a result, decision-making essentially becomes a classical Boolean system that only accepts clear, discrete inputs. It loses the flexibility to consider fuzzy or partially associated inputs, which makes it less adaptable and less accurate in handling uncertainty. In the lower section of the table, we contrast scenarios with significantly divergent values, showing that the baseline simply adjusts priorities in response to strong variations.

5.6.2. Evaluation: Route Selection

In the scenario in Figure 21, where one drone is required to move from point A to point B and multiple routes are proposed by the flight management system, the selection of an appropriate route based on different parameters is mandatory. Each route provides valuable information, such as distance and population density, to make informed decisions based on preferences and priorities. The most simple and intuitive route (red) is straightforward, following a direct line, but this drone then moves directly over the city, potentially posing risks. The orange route avoids houses but still crosses the city streets, with a reduced likelihood of hazards. Similarly, the blue route tries to avoid the city. The final routes (green and yellow) take a wide tour around the city, flying over only a few houses and streets, making it the safest but also the most costly in terms of efficiency.

Figure 21. Five distinct route suggestions are proposed for a delivery drone, each differing in safety levels and distance to the target. The starting location is denoted by A, while B represents the target.

The decision-making process for both approaches is outlined in Table 6. We maintain the battery parameter b at fixed levels of 5%, 20%, 35%, 50%, 65%, and 80%. The density aspect of the route parameter is determined based on expert knowledge, while the distance is measured. We specify route 1 as red, route 2 as orange, route 3 as blue, route 4 as green, and route 5 as yellow.

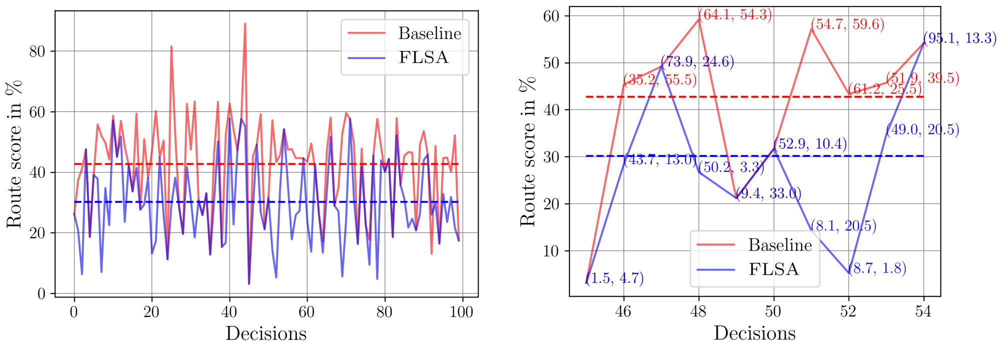
Initially, with lower battery levels, the shortest-distance route is selected. As battery capacity increases incrementally, longer routes become better choices, offering enhanced safety due to lower population density. The baseline primarily recommends three routes while disregarding others that are available. Conversely, the proposed approach selects the most suitable route based on the current drone conditions. In the final scenario, with 80% battery capacity, the baseline selects the second route, thereby increasing risk, whereas battery power is available in order to choose a less risky route. With increasing battery levels, the FLSA prioritizes those with greater distances but lower population densities. To select the appropriate path based on the circumstances, begin by following the path sequentially from one.

In light of our empirical validation confirming the significant role of battery level in the decision-making process, the subsequent focus shifts toward evaluating the selected routes. To this end, we generate n random sets of density and distance values, each sampled from a uniform distribution within the interval $[0, 100)$, representing potential routes. In this context, the route score denotes a route's characteristic, specifically represented by the mean value of density and distance. Lower values signify superior scores, as both parameters are directly proportional. The resulting decisions from both algorithms include individual data points on a graph.

In Figure 22, we present an evaluation focusing on a constant battery level of 50%. Within the magnified section, we augment the graph with brackets encapsulating the attributes of the selected route, namely density and distance. The straight line delineates the average performance values. Overall, the proposed methodology exhibits superior performance under a 50% battery condition. To comprehensively explore its behavior across varying battery levels, we depict the results through boxplots in Figure 23 with different amounts of optional routes. Therefore, we conducted an evaluation of the algorithms across 100 distinct scenarios. For each scenario, we generated sets of 5, 10, 15, and 20 proposed routes. The parameters for each route, specifically urban density and distance, were sampled from a uniform distribution within the range [0, 100). Furthermore, the battery level parameter was systematically varied from 10% to 90% in increments of 20%.

Table 6. Evaluation of the route selection using the baseline and FLSA with normalized input parameters. Route 1: red; route 2: orange; route 3: blue; route 4: green; and route 5: yellow. The highest scores, highlighted in bold, represent the selected route.

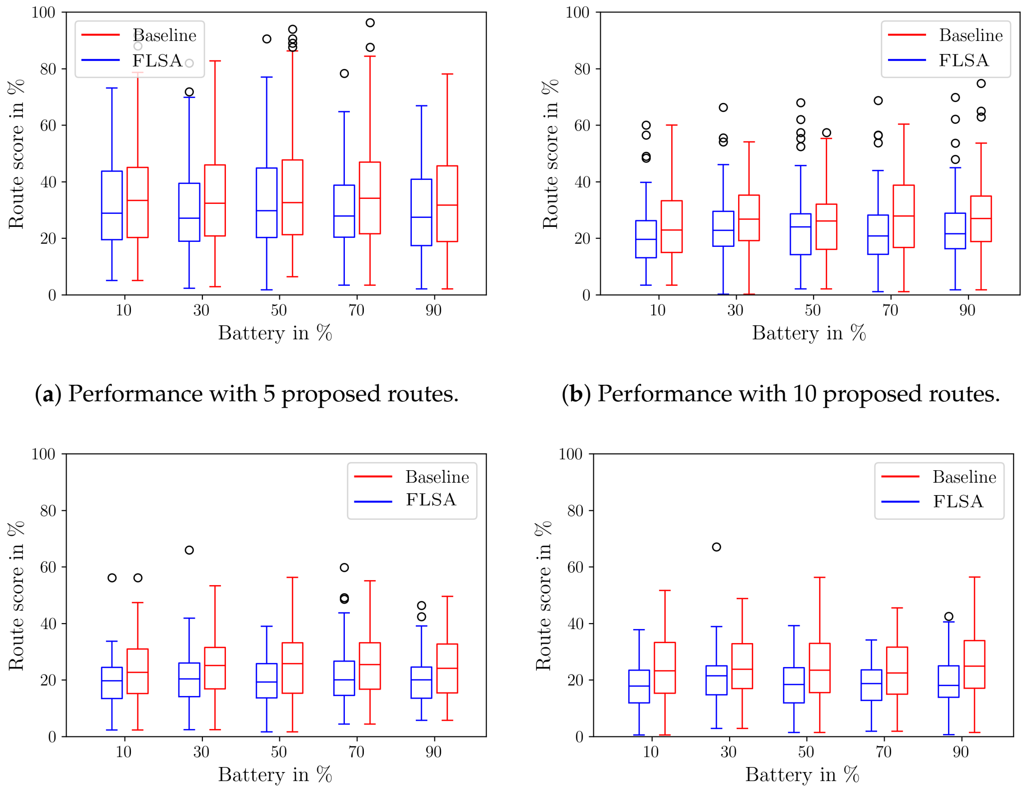
Index	Parameters		Scores ($b = 5\%$)		Scores ($b = 20\%$)		Scores ($b = 35\%$)	
	Density	Distance	Baseline	FLSA	Baseline	FLSA	Baseline	FLSA
1	100	19.20	**47.5**	**39.295**	**47.5**	**38.747**	43.784	46.963
2	71	34.96	0.0	37.532	0.0	37.532	0.0	**54.755**
3	49	48.26	6.333	7.8	6.333	8.516	**93.0**	42.561
4	28	72.82	6.333	6.333	6.333	6.333	30.0	24.89
5	8	100	6.333	6.333	6.333	6.333	30.0	21.901
Index	**Parameters**		**Scores ($b = 50\%$)**		**Scores ($b = 65\%$)**		**Scores ($b = 80\%$)**	
	Density	**Distance**	**Baseline**	**FLSA**	**Baseline**	**FLSA**	**Baseline**	**FLSA**
1	100	19.20	43.784	46.905	43.784	36.53	6.333	6.333
2	71	34.96	0.0	45.09	0.0	41.395	**70.0**	14.022
3	49	48.26	**93.0**	**71.543**	**93.0**	46.72	43.784	30.0
4	28	72.82	30.0	44.522	30.0	**54.063**	66.673	65.616
5	8	100	30.0	36.783	30.0	52.858	66.673	**71.667**



(**a**) 100 random decision-making scenarios. (**b**) Zoomed decisions scenarios.

Figure 22. Evaluation of the two algorithms in 100 scenarios using a battery level of 50% and randomly sampled values of the route parameters (urban density, distance) for each route. (**a**) has been zoomed in to detail the characteristics of the selected routes in (**b**).

In all experiments, the proposed algorithm demonstrates superior performance by selecting more appropriate routes. This is evidenced by consistently lower mean values and reduced variance, as indicated by narrower boxplots. The performance advantage of the FLSA becomes more noticeable with an increasing number of potential random routes. Additionally, both algorithms show improved performance with a greater number of random routes, as the likelihood of finding better routes increases with the size of the route set. By using this process, we are able to generate informed decisions rooted in the complex rule-based combination of interconnected parameters within the framework. This capability not only amplifies the effectiveness of our experimental results but also enlarges their relevance and practicality across various scenarios. Consequently, we can navigate complex decision landscapes with a high level of precision and confidence, enabling advancements in our understanding and application of rule-based principles.



(**a**) Performance with 5 proposed routes. (**b**) Performance with 10 proposed routes.

(**c**) Performance with 15 proposed routes. (**d**) Performance with 20 proposed routes.

Figure 23. Boxplot evaluation of the two algorithms in 100 scenarios. We sample the route parameters (urban density, distance) from a uniform distribution on the interval [0,100) and sweep the parameter battery level. Circles represent outliers.

6. Discussion

We have successfully employed a ruled-based algorithm for decision making in diverse drone logistic challenges. The achieved results reveal the system's effectiveness in handling complex tasks, such as task assignment, route planning, and priority determination. The configuration of the system is designed with simplicity and user-friendliness in mind. This approach ensures that users, regardless of their technical expertise, can easily tailor the system to their specific needs. The decision to implement the ruled-based algorithm underscores the commitment to providing an adaptable, efficient, and easily deployable solution. This implementation choice enhances the practicality and ease of integration into various drone-related applications. Moreover, the system can be triggered using events, such as when one drone intrudes the safety zone of another drone, initiating the priority calculation. Alternatively, a simple frequency-based mechanism can also run the approach. For instance, the dynamic resizing of the safety zone, which adjusts regularly based on the drone's speed, can be seamlessly accommodated through this mechanism.

While the current study marks a significant step forward in applying decision-making algorithms to drone-related applications, potential avenues for future research should be explored. One research direction involves utilizing neuro-fuzzy systems to integrate neural network learning capabilities, enhancing computational models' adaptability and power. Another future research involves expanding this framework to accommodate a multimodal drone airline, incorporating various parameters across different modalities.

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