Decentralized Distribution of UAV Fleets Based on Fuzzy Clustering for Demand-driven Aerial Services

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***Abstract*—Unmanned aerial vehicles provide a flexible solution for emerging civilian applications such as last-mile delivery, remote environmental monitoring or hazard detection. However, since the demand for this type of applications is sparsely distributed and comprises spatiotemporal uncertainty, prior to the deployment of aerial means, the dimension and configuration of multi-UAV systems has to be addressed. This paper proposes a clustering-based dimensioning strategy for networks of aerial vehicles, that incorporates heterogeneous vehicle characteristics and energy-related autonomy constraints to determine the type and number of vehicles required to meet a given demand. The approach follows a fuzzy data-driven method which enables generating coverage regions with elastic boundaries that allows for cooperation between neighboring regions to manage high and low demand scenarios, providing improved resilience to demand fluctuations and guaranteeing a well-conditioned formulation for the optimal resource allocation problem.**

***Index Terms*—unmanned aerial vehicles, demand-driven systems, fleet management, decentralized networks, fuzzy clustering**

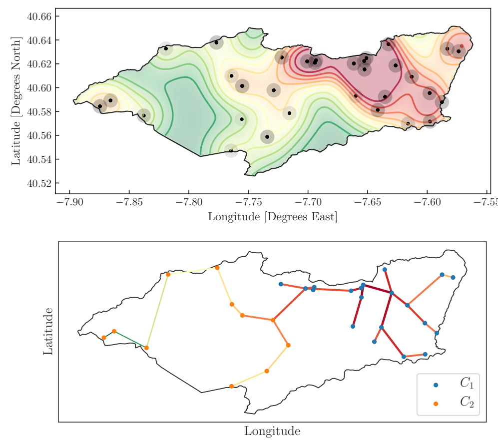

Fig. 1: Demand-driven clustering for multi-UAV fleets.

I. Introduction

The pressing challenges faced in modern societies to address emergency response operations, remote environmental monitoring or on-demand delivery are opening a broad scope of novel civilian applications of unmanned aerial vehicles (UAVs) [1]. For this reason, there has been increased research interest in developing multi-UAV systems to perform autonomous missions, providing a cost-efficient solution to carry out valuable tasks. In that sense, the advances in robotics are paving the way for future aerial networked systems that comprise a resilient mobile infrastructure capable of adapting to dynamic events in real-time.

In this context, the optimization of multi-UAV systems can be casted as a combinatorial problem and several variations of classical formulations have been proposed *e.g. Traveling Salesman Problem* [2], [3], *Vehicle Routing Problem* [4], or *Orienteering Problem* [5]. However, although extensive research has been devoted to address this issue from a resource allocation standpoint, in which a set of fixed resources has to be assigned to tasks, these approaches formulate the problem under the assumption that the resources of the system are able to satisfy the tasks to be performed. In that sense, it is implied that the endurance of the available vehicles is sufficient to provide adequate coverage to a fixed area. In general, works do not delve into the question of how to dimension the system, which is essential to ensure the problem is not ill-conditioned.

Hence, the problem of dimensioning multi-UAV systems requires considering a wider scope, because the optimization of resources in vehicle assignment scenarios encompasses a chain of decisions on different levels and temporal scales:

i) *strategic level*: long-term design decisions related to the dimension of the fleet, *e.g.*, the number of vehicles in the network, the type of vehicles and desired characteristics;
ii) *tactical level*: mid-term planning decisions regarding network configurations for different demand scenarios and deployment strategies, targeting availability and costs;
iii) *operational level*: short-term operational decisions concerning vehicle routing, scheduling strategies and trajectory optimization for mission-oriented performance.

These aspects are highly intertwined because flight time is dependent on vehicle characteristics, as well as deployment and demand locations. These parameters drive how the system is able to respond to fluctuations in the stochastic demand, but are rarely explicitly handled in resource optimization.

To bridge this gap, this paper focuses on strategic and tactical levels, by addressing the dimensioning and design of multi-UAV systems, focusing on demand-driven network optimization based on fuzzy clustering, illustrated in Fig. 1.

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The proposed approach is threefold: *i)* it builds decentralized networked systems based on cluster-based partitioning using fuzzy clustering to ensure adequate area coverage in the region of interest; *ii)* within each cluster, inner-clusters based on hierarchical density structure are extracted to dimension the multi-UAV fleets with adequate vehicle-types; and *iii)* the fleet configurations are designed to satisfy the demand.

This work contributes to the state-of-the-art by proposing fuzzy partitioning policies that incorporate heterogeneous vehicle characteristics and energy constraints into the cluster optimization process. The principal advantage of this method is that its ability to cope with data uncertainty enables generating coverage regions with elastic boundaries which allows cooperation between neighboring regions to manage high and low demand scenarios. To explore this approach, this work analyzes a case-study focused on area coverage in wildfire detection and monitoring scenarios, namely in surveillance missions and active fire monitoring. From a resource optimization perspective, the proposed framework for dimensioning and design of UAV fleets simplifies the problem formulation stage, because by following a data-driven method it ensures a well-dimensioned system. The outcomes produce improved resilience to spatial variation in demand, as well as fluctuations in the temporal intensity of the events.

In the sequence, this work is organized as follows: Section II introduces the problem statement and demand modeling approach. Section III presents clustering-based partitioning methods. Section IV focuses on the optimization of the decentralized network structure, followed by the analysis of results in Section V. To conclude, Section VI overviews the core takeaways and discusses possible directions of future research.

II. Demand-Driven Network Optimization

Networked aerial systems can enable a mobile infrastructure to support a multitude of applications involving the coverage of extensive areas, by having the capability of adapting in response to dynamic events. However, UAVs have stringent energy constraints that limit flight endurance, imposing the need to optimize the distribution of multi-UAV fleets.

Furthermore, considering missions are distributed over large areas and have a great degree of uncertainty on spatial and temporal levels, it is important to establish *a priori* demand models in order to design systems with an adequate amount of vehicles and deployment locations so as to avoid over-dimensioned or under-dimensioned systems, and promote fault-tolerance in dynamic scenarios. To that end, the following establishes the problem statement, as well as the demand modeling approach.

A. Problem Statement

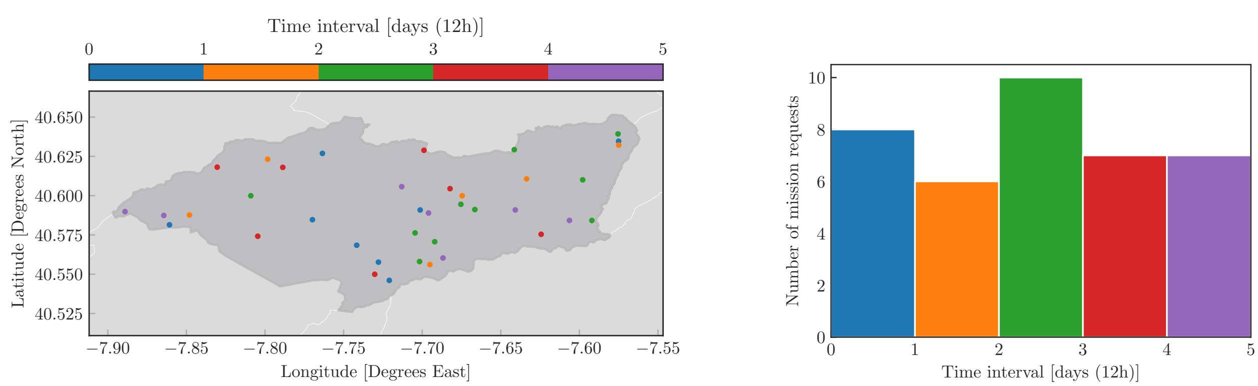
Consider a heterogeneous fleet, letting $\mathcal{V} = \{1, \dots, K\}$ represent the types of vehicles employed, and $\mathcal{V}_k$, define the subset of vehicles of type k. The fleet is composed of m_k vehicles of each k type, and the sum of the cardinality of each subset $\mathcal{V}_k$ gives the total number of vehicles of the fleet. In this work, two types of low-altitude UAVs are considered, namely multi-rotors and fixed-wing drones.

The discrete domain of aerial services tasks can be described using the mathematical formalism from graph theory, where in a graph, $\mathcal{G} = (\mathcal{N}, \mathcal{E})$, the locations are represented by a set of nodes, $\mathcal{N}$, and the paths between locations are denoted by a set of edges, $\mathcal{E}$. To formulate the network optimization problem in a decentralized form, the set of locations $\mathcal{N}$ is partitioned into clusters to build partial subgraphs. Let the objective function of the global problem, F_G, be defined by the cumulative sum of the local problems $F_i(x_i)$. The problem can then be stated as:

$$\min_{\mathbf{x}} \quad F_1(x_1) + F_2(x_2) + \cdots + F_c(x_c) \tag{1}$$

where $\mathbf{x} = [x_1, x_2, \dots, x_c]$ and c denotes the number of clusters. The core advantages of adopting a decentralized approach consist of increased fault-tolerance and flexibility, as well as reduced computational burden. The local cost functions, which incorporate density-based and energy-related components associated to the different vehicles, are formalized further along in section IV.

The principal goal is to optimize the type and distribution of UAVs in fleets able to perform on-demand missions that are sparsely distributed over a geographical region, as exemplified in Fig. 2a.



(a) Spatiotemporal distribution

(b) Demand profile

Fig. 2: Example of demand forecasting for a 5-day time horizon: (a) distribution of aerial services according to homogeneous Poisson point process; (b) demand profile for each time interval, $\mathcal{T}$, considering each day with 12-hour operational time.

Considering that geographical administrative boundaries are highly asymmetric, an unsupervised clustering approach is a well-suited approach to derive the structure of the fleets based on probabilistic demand. To that end, the following presents the demand modeling approach for scenarios of interest.

B. Demand Modeling

The demand of aerial services can be modeled as a stochastic process describing a spatiotemporal pattern. For that purpose, this work employs a Poisson point process, which is widely used to model random events. Applications include *e.g.* modeling occurrences of natural hazards such as earthquakes or wildfires, on spatial and/or temporal levels, or representing the arrival of customer orders at a service provider [6].

In that sense, it is assumed that the requests, represented by location and request time, $L(x, y, t_R)$, are independent random variables, which for a given time interval, $\mathcal{T}$, have constant average spatial rates of occurrence for a bounded area, A, and that the average rate (requests per time period) is constant.

The spatial demand is represented according to a discrete Poisson distribution, f_{Pois}, that models the probability of a discrete number of requests, n, occurring in a time interval for a specific bounded area:

$$f_{\text{Pois}}(n; \mu_s \in \mathbb{R}^+) = \Pr(X = n) = \frac{{\mu_s}^n e^{-\mu_s}}{n!} \tag{2}$$

with the constant expected value, μ_s, depending on the spatial intensity of the demand and area size, *i.e.*, $\mu_s = \lambda_s A$. The spatial intensity, λ_s, is the expected average number of tasks per unit area. The spatial locations can be described with *e.g.*, longitude, latitude coordinates or transformed into cartesian space. In this context, the sampling of the Poisson distribution for several time intervals yields a demand profile for a *time horizon* considered in the problem, for instance as is illustrated in Fig. 2b, for a forecast with a 5-day time horizon.

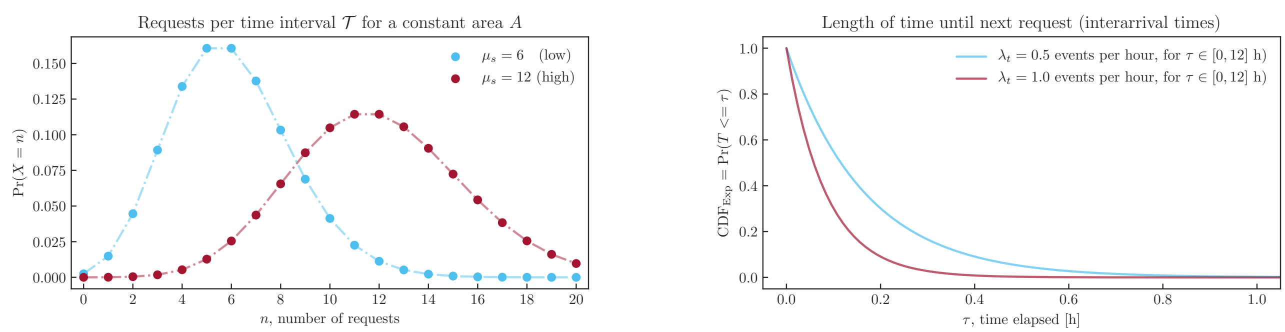
The temporal uncertainty of the demand is described by the variability in the interval of time between consecutive requests, *i.e.* the *interarrival times*, T. In a Poisson point process these time increments are independent and identically distributed random variables that follow a continuous decaying exponential distribution. Then, the interarrival times, T, are obtained using the inverse of the cumulative distribution function of the exponential distribution, $[F_{\text{Exp}}]^{-1}$, as follows:

$$F_{\text{Exp}}(\tau; \mu_t) = \Pr(T \leq \tau) = \int_0^{\tau} \mu_t e^{-\mu_t t} dt = 1 - e^{-\mu_t \tau}$$
$$\left[F_{\text{Exp}}(\tau; \mu_t)\right]^{-1} = -\frac{ln(1-\tau)}{\mu_t} = T \tag{3}$$

with μ_t denoting the average rate per time sampling, which is a function of the temporal intensity, λ_t, and time window size, τ. The temporal intensity, describes the average number of tasks per unit time. For instance, taking the example of Fig. 2b, a time interval of one day, $\mathcal{T}$, with 8 mission requests, can have a temporal intensity of 0.5 events per hour for a time window, τ, of 12-hour period. In this way, by finding the number of requests in each day according to the Poisson distribution (2), for each event in that interval $\mathcal{T}$, the interarrival time is determined through (3) based on a random uniform distribution, with $\tau \sim \text{Unif}(0, 1)$. Note that the sum of interarrival times can not exceed the defined time interval, $\mathcal{T}$, so the values are sampled as to not exceed this upper bound.

1) Load Level: To establish different load levels, high and low workload scenarios are modeled by selecting distinct spatial and temporal intensities. The definition of these parameters is intrinsically related to the process under study and the time horizon considered. Herein, the process will be considered stationary, *i.e.* the average spatial and temporal intensities do not vary throughout the time-horizon (forecast window). This premise is valid assuming demand scenarios that occur in short periods in a specific region. Nevertheless, in reality, spatial and temporal intensities are expected to vary depending on the application, seasonality and geographic region.

Since aerial services are highly constrained by the limited autonomy of UAVs, the way spatial intensity relates to the area covered plays an important role in establishing decentralized multi-UAV networks. Therefore, testing different workload levels is essential for the analysis of the dimensioning problem because it drives the total number of missions that have to be performed and in result influences fleet size and the operation area of the fleet. Fig. 3 depicts distributions with different intensity levels used to simulate high and low workloads.



(a) discrete Poisson distribution for mission requests

(b) exponential distribution of interarrival times

Fig. 3: Demand modeling with Poisson point process: (a) spatial uncertainty modeled with Poisson distribution represents the variability of the number of requests occurring per time interval in a specific area; (b) temporal uncertainty concerns the variability in the time between requests, modeled with a continuous decaying exponential distribution.

2) Process Type (homogeneous vs. nonhomogeneous): The spatial structure of Poisson point processes can have distinct distributions, which for this problem influences how the mission requests are spread over the area of interest. For the homogeneous case, the spatial coordinates (x, y) are generated by a uniform distribution within the limits of the specified bounded area A, defined as a polygon or a multi-polygon. In turn, for the nonhomogeneous or inhomogeneous case, the spatial coordinates can be generated by a spatially varying deterministic intensity function $\Lambda(x, y)$, through a *thinning procedure* of a homogeneous point process of intensity $\lambda_{\max}$, where points are eliminated or retained according to a probability which depends on spatial location, $p(x, y)$ [6]. An example of the difference between homogeneous and nonhomogeneous processes is presented in Fig. 4 with the following intensity function for the nonhomogeneous case:

$$\Lambda(x, y) = 2(x^2 + y^2) \tag{4}$$

$$p(x, y) = \Lambda(x, y)/\lambda_{\max} \tag{5}$$

In this context, these differences allow simulating in a generic sense *e.g.* patrolling missions where a large area has to be monitored periodically (homogeneous), or active fire monitoring scenarios where mission requests are more likely to be concentrated in a particular area (nonhomogeneous). Hence, for comparison purposes the thinning process is implemented with a stop criterium to halt when the number of requests matches the load level from the Poisson distribution, enabling the evaluation of different processes with the same load level.

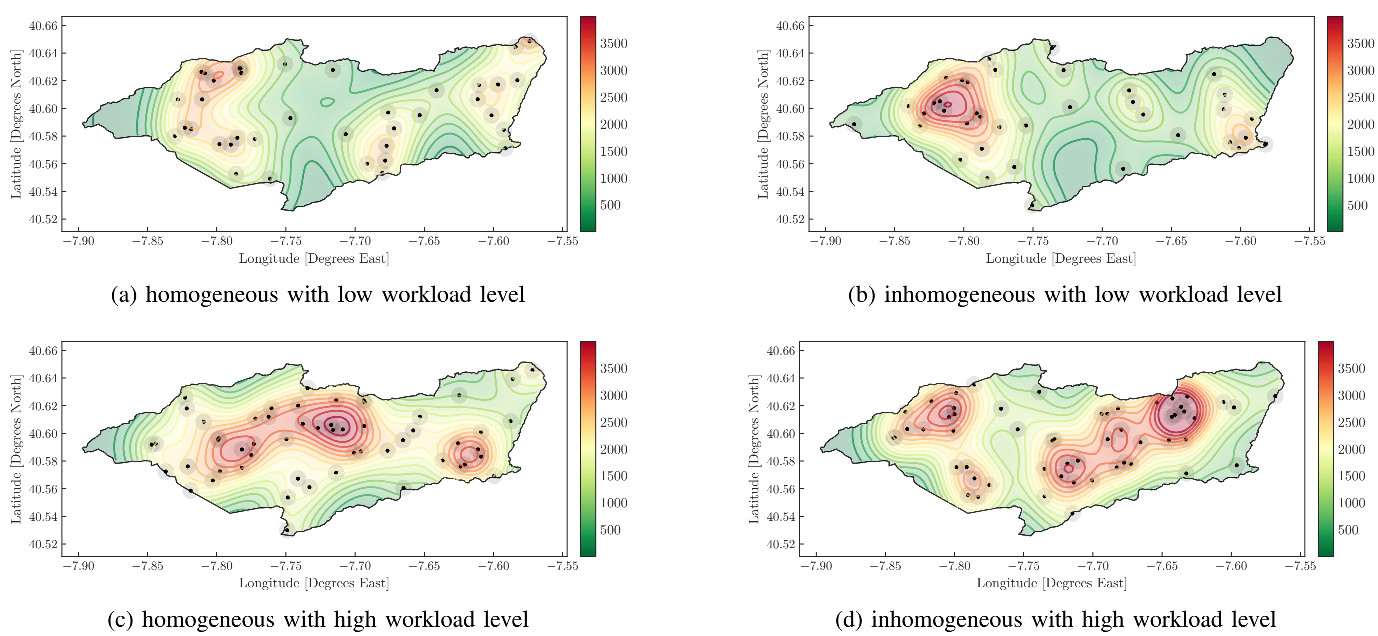
In this way, the parametrization of the *load level* and *process type* allows modeling the demand and generating the mission requests for simulation. Considering different vehicle types have distinct flight endurance characteristics, the density of mission requests will impact the optimization of the configuration of multi-UAV fleets. For instance, the high maneuverability is one advantage of multi-rotor drones, however this reduces the flight endurance, thus restricting missions to a limited range. Conversely, fixed-wing drones have the benefit of harnessing the aerodynamic lift, which enables longer flights. Therefore, for short-range missions in an area with higher number of missions multi-rotors are more well-suited, whereas for performing long-range missions fixed-wing drones are a better alternative. For these reasons, the way the requests are spread has to be subsequently estimated.

3) Demand Density: To measure the density of requests per unit area, *i.e.* an estimate of the spatial intensity function of the point pattern, this work uses kernel density estimation (KDE) based on the convolution of isotropic Gaussian kernels [7]–[9].

Let $\mathbf{L} = \{\ell_1, \ldots, \ell_n\}$ denote the request locations in bidimensional (2D) space, belonging to a bounded area A. The fixed-bandwidth kernel density estimate of the intensity function, *i.e.* the local intensity estimate at location p_i, is given by:

$$\hat{\lambda}(p_i) = \frac{1}{nh^2} \sum_{i=1}^{n} \kappa \left(\frac{p_i - \ell_i}{h} \right) e(p_i)^{-1} \quad p_i \in A \tag{6}$$

where κ denotes the 2D Gaussian smoothing kernel, $h > 0$ is the smoothing parameter (*i.e.* the bandwidth), and $e(p_i)$ represents an edge-correction factor [10]. Note that herein the temporal data is not considered for density estimation, as the multi-UAV fleets are to be dimensioned for the period of the time horizon, in this case based on a 5-day forecast. Recalling Fig. 4 comparing variable spatial distribution and load levels, the density estimation enables identifying zones with a higher number of mission requests as described by the color schema.



(a) homogeneous with low workload level

(b) inhomogeneous with low workload level

(c) homogeneous with high workload level

(d) inhomogeneous with high workload level

Fig. 4: Demand distribution comparison for a 5-day period: (a) and (b) homogeneous (uniform), with low and high load, respectively; (c) and (d) nonhomogeneous, with low and high load, respectively;

Albeit having a greater computational cost than alternative density estimation techniques, KDE has the benefit of considering the spatial distribution over complete neighborhoods in the region of interest. Conversely, proximity-based core measures tend to produce myopic density estimates, biased by local information. The following sections delve deeper into this issue, and outline the proposed demand-driven clustering approach designed to: *i)* build decentralized multi-UAV networks and *ii)* design the configurations of multi-UAV fleets.

III. Clustering-based Graph Partitioning

The problem of deploying UAVs to perform surveillance or monitoring tasks over extensive areas lends itself to be easily represented by a graph. However, if the problem has a high number of aerial services to perform, the subsequent resource allocation problem will become very complex, if feasible at all. Indeed, due to the energy constraints of aerial platforms, the universe of discourse of the entire problem results in many unfeasible solutions in practice.

To handle this issue, a decentralized approach is proposed based on clustering methods, which divides the problem into multiple subgraphs, enabling solving simpler problems in parallel by limiting the size of the search space. From an optimization standpoint the main advantage is that the search of feasible solutions is more effective at a reduced computational burden. In addition, this approach increases control over fleet dimensioning and design, whilst making the decentralized system more flexible and fault-tolerant.

Clustering algorithms are generally unsupervised learning techniques that allow grouping data according to different objectives [11]. This allows dividing the problem space using characteristics intrinsic to the data. Herein, based on the demand-driven modeling approach adopted, the interest centers on centroid-based clustering and hierarchical clustering.

While centroid-based clustering methods, *e.g.* K-means [12], [13] or Fuzzy C-Means [14]–[16], focus on partitioning the space in a balanced volume per cluster in terms of area coverage, this approach disregards cardinality, shape and density of each cluster, *i.e.* if there are many or few aerial tasks to perform, how are these distributed and concentrated in space, respectively. Conversely, clustering based on distance-based density measures, such as DBSCAN [17], [18] or hierarchical extensions HDBSCAN [19], concentrate on extracting cluster structures without restricting the maximum cluster volume.

In the context of the problem, considering flight endurance limitations, volume-constrained partitioning is critical to ensure adequate area coverage of the region of interest. In turn, to determine the fleet configurations, proximity-based density and hierarchical information are important to select suitable vehicle types. Thus, combining both alternatives is essential, but given the spatiotemporal uncertainty in the data, a soft clustering approach is better suited to address this problem.

In that sense, this work proposes a decentralized distribution framework based on fuzzy clustering, which incorporates density and hierarchical information, that enables dimensioning and designing a flexible multi-UAV fleet system capable to adapt to stochastic demand. More specifically, the first stage consists in a fuzzy partitioning policy based on distance-based fuzzy clustering that encompasses spatial and density information, using the Gustafson-Kessel fuzzy clustering algorithm [20]. Subsequently, the second stage concerns deriving clusters within each main subgraph using HDBSCAN based on proximity-based density information, namely mutual reachability distance and hierarchical structure. The following describes the graph model and the main components of the proposed three-stage clustering algorithm, and how these relate to the proposed framework for dimensioning and design of multi-UAV fleets.

A. Graph Model

The demand dataset is defined in the LLA (Latitude, Longitude, Altitude) referential and are subsequently converted to the NED (North, East, Down) coordinate system. The demand density at each location is estimated using the KDE method at each service waypoint. Given a set of N samples, and a data vector $\mathbf{z}_k = [X, Y, Z, \hat{\lambda}]^T$, defined by the NED coordinates and KDE-based density, let $\mathbf{Z} = [\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_N]$ define the dataset of demand waypoints of the aerial services to be performed. The proposed methodology employs a two-stage clustering algorithm, thus the graph model undergoes transformations throughout the algorithm. The following definitions relate the key components in this demand-driven approach.

1) Distance Measures:

- Mahalanobis distance is employed in the GK algorithm to allow for clusters with different shapes but identical area;
- Core distance based on the Euclidean distance to the n-th neighbor, is used to compute the mutual reachability distance (MRD), to retrieve proximity-based density estimates and hierarchical structure of the clusters.

2) Demand Density Estimates:

- KDE density conveys the number of missions in the region of interest;
- MRD density translates the proximity of nearby missions;

Further vehicle-related aspects are presented in section IV.

B. Gustafson-Kessel Fuzzy Clustering

To derive fuzzy data partitions from a set of locations $\mathcal{N}$, the Gustafson-Kessel (GK) fuzzy clustering algorithm clusters each data point based on centroid-based distances, according to a degree of membership, μ_{ik}, forming the fuzzy partition matrix, $\mathbf{U} = [\mu_{ik}]$. This allows locations at the boundary of each clustered region to belong to more than one fuzzy set. The algorithm computes the clusters centers, $\mathbf{v}_i$, as:

$$\mathbf{v}_i = \frac{\sum_{k=1}^{N} (\mu_{ik})^m \mathbf{z}_k}{\sum_{k=1}^{N} (\mu_{ik})^m}, \qquad i = 1, 2, \dots, C \tag{7}$$

defining the matrix of cluster centers $\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_C]$. The overlap between clusters is given by the fuzziness parameter, $m \in [1, \infty)$, with the lower bound equal to 1 corresponding to a hard partition. The number of clusters, C, is defined heuristically as a function of the area to be covered, and the fuzziness parameter m, through a grid search procedure.

The GK algorithm uses an adaptive distance measure based on the Mahalanobis distance, a squared inner-norm, given by:

$$D_{ik\mathbf{A}_i}^2 = (\mathbf{z}_k - \mathbf{v}_i)^T \mathbf{A}_i (\mathbf{z}_k - \mathbf{v}_i) \tag{8}$$

where $\mathbf{A}_i = |\mathbf{F}_i|^{\frac{1}{n}} \mathbf{F}_i^{-1}$ is a norm-inducing matrix based on the fuzzy covariance matrix, $\mathbf{F}_i$, given by:

$$\mathbf{F}_i = \frac{\sum_{k=1}^{N} (\mu_{ik})^m (\mathbf{z}_k - \mathbf{v}_i)(\mathbf{z}_k - \mathbf{v}_i)^T}{\sum_{k=1}^{N} (\mu_{ik})^m} \tag{9}$$

The GK algorithm, in addition to $\mathbf{U}$ and $\mathbf{V}$, also uses the matrices $\mathbf{A} = (\mathbf{A}_1, \ldots, \mathbf{A}_C)$ as optimization variables, to allow varying the shape of each cluster while maintaining a fixed volume, ensuring each multi-UAV fleet will cover equivalent areas. Thus, the clustering criterion to minimize is given by the objective function:

$$J(\mathbf{Z}; \mathbf{U}, \mathbf{V}, \mathbf{A}) = \sum_{i=1}^{C} \sum_{k=1}^{N} (\mu_{ik})^m D_{ik\mathbf{A}_i}^2 \tag{10}$$

The partition matrix $\mathbf{U}$ is updated in a iterative process, by updating the membership degrees, computed as:

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{C} \left(\frac{D_{ik\mathbf{A}_i}}{D_{jk\mathbf{A}_i}} \right)^{2/(m-1)}} \tag{11}$$

halting if the improvement on the cost function satisfies a given tolerance, or if the maximum number of iterations is reached.

By applying this technique it is possible to partition the problem and build decentralized networks with fuzzy boundaries for increased flexibility. In the sequence, within each cluster we aim to extract the demand structure so that multi-UAV fleets are designed with suitable configurations, *i.e.* how many drones and of which type, *e.g.* fixed-wing or multi-rotor.

C. Hierarchical Density-based Clustering

Considering that multi-rotors have limited flight endurance, these are better suited for short-range missions, even if within that range there exists a high number of service requests. Conversely, fixed-wing drones can serve long-range missions more effectively. In that sense, the nature of the demand influences the selection of type of vehicles within each fleet.

To match the demand structure, *i.e.* if it is sparsely/densely distributed, to better suited fleet configurations, this work employs partly a density-based method, the HDBSCAN. The following describes the central aspects of this method, while subsequent sections focus on the algorithm proposed to address this problem. First, the problem space is transformed to represent density information, through a proximity measure termed mutual reachability distance, d_{mreach}. To that end, for each $\mathbf{z}_k \in \mathbf{Z}$ a density estimate is computed, denominated the core distance to the n-th nearest neighbor [21], which for the sake of simplicity we represent as d_{core}, and without loss of generality since n is an input parameter. With the mutual reachability distance between sample j and k given by:

$$d_{\mathrm{mreach}}(\mathbf{z}_j, \mathbf{z}_k) = \max \left\{ d_{\mathrm{core}}(\mathbf{z}_j), d_{\mathrm{core}}(\mathbf{z}_k), d(\mathbf{z}_j, \mathbf{z}_k) \right\} \tag{12}$$

a weighted graph based on the MRD is established for $\mathbf{Z}$, from which a minimum spanning tree (MST) is computed [22].

To extract the cluster structure, a dendrogram is constructed from the MST of graph of the mutual reachability distance, $\mathcal{G}_R = (\mathcal{N}, \mathcal{A})$. Subsequently, based on a specified minimum cluster size the cluster hierarchy is condensed to obtain a locally aggregated version of the demand. However, the hierarchical approach alone does not suit well this problem.

IV. Decentralized distribution of m-UAV fleets

The first stage of the proposed algorithm (Algorithm 1) consists of the partitioning of the problem space using fuzzy clustering to create decentralized networks described by subgraphs. Secondly, following a decentralized approach, the procedure to extract hierarchical structure of the inner-clusters applies to the set corresponding to each fuzzy cluster, denoted by $\mathbf{Z}_i$ with $i = 1, 2, \ldots, C$. Then, having density-based inner-clusters, the main goal is to design the fleet configurations with the appropriate characteristics to respond to demand. To that end, recall the global objective function (1). For each operating area, *i.e.* each fuzzy cluster, the local cost, F_i is evaluated by:

$$\min \sum_{k \in \mathcal{V}} \sum_{m \in \mathcal{V}_k} \sum_{(i,j) \in \mathcal{A}} d_{ij} x_{ij}^{k,m} + \sum_{k \in \mathcal{V}} \sum_{m \in \mathcal{V}_k} e_k v_{k,m} \tag{13a}$$

$$\text{s.t.} \quad x_{ij}^{k,m} \in \{0,1\}, \ \forall (i,j) \in \mathcal{A}, \forall k \in \mathcal{V}, \ \forall m \in \mathcal{V}_k \tag{13b}$$

$$v_{k,m} \in \{0,1\}, \ \forall k \in \mathcal{V}, \ \forall m \in \mathcal{V}_k \tag{13c}$$

with the binary decision variables representing the allocation of a vehicle in a inner-cluster, $x_{i,k}^{k,m}$, that is 1 if vehicle m of type k is allocated, or null otherwise, and the deployment of vehicle m of type k, $v_{k,m}$, that is 1 if a vehicle is deployed and assigned a cluster, and zero otherwise. The objective function balances two goals, namely the allocation of best suited vehicles for each demand density structure based on distance, d_{ij}, and the minimization of energy expenditure, accounting for a energy cost, e_k, for each vehicle deployed, $v_{k,m}$.

A. Cluster Optimization and Validity Conditions

Operational areas can not violate minimum service levels, which relate to the maximum vehicle range and expected demand, λ. Thus, the area of the region of interest, A, has to be divided into equivalent-sized clusters, according to the operational area ratio given by $\gamma = A \cdot \lambda / \max_{\mathrm{range}}$. Thereby, the number of clusters can be computed heuristically, as $C = \gamma \cdot m^s$, with m representing the overlap between clusters, and where s denotes a safety/redundancy parameter. This allows increasing the flexibility and fault-tolerance of the networked system, depending on the application requirements. Since $m \in [1, \infty)$ with 1 corresponding to a hard partition, for $s > 0$ the redundancy of the system is increased, because the number of clusters is overdimensioned. In turn, for $s < 0$ the system will be less flexible as with constant overlap between clusters, the number of clusters decreases, the cluster volume increases. Since the areas to be covered expand, the number of vehicles required to meet the minimum service level also increases, but the ability to share resources does not, so the system will be less capable of adapting to demand fluctuations.

B. Design of Fleet Configurations

With the minimum spanning tree of the mutual reachability distance, this estimate of local density is leveraged to determine the type of vehicle that should be allocated to that aerial service. As mentioned throughout this work, multi-rotors (MR) are preferential for short-distance missions, whereas fixed-wing (FW) drones will be preferentially allocated to long-distance tasks. To build solutions for fleet configurations, the average of the MTS weights allows assessing if the tasks are in a dense/sparse area, which enables knowing if a MR or a FW should be selected, respectively. When vehicle maximum flight endurance is exceed, additional aerial vehicles are added.

Therefore, with this iterative process, solutions for each cluster can be composed by a single type of vehicle, *e.g.* either fixed-wing or multi-rotor drones, or result in heterogeneous configurations with both types of vehicle in the same multi-UAV fleet. By optimizing the types of vehicles deployed according the to the nature of the demand, and by having fuzzy overlap between clusters, the solutions will allow sharing of resources between neighboring regions to manage fluctuations over time in demand, and consequently in the fleet load level.

Algorithm 1: Demand-driven clustering for multi-UAV networks

data : $\mathbf{Z} = [\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_N]$, dataset with $k = 1, 2, \ldots, N$ samples; $\mathcal{S}$, scenario parameter dictionary
$\mathbf{z}_k = [X, Y, Z, \hat{\lambda}]^T$ in NED coord. and density estimate;
input : m, overlap degree between clusters; γ, operational area ratio; n, core distance parameter, c_{min}, minimum cluster size
output: $\mathbf{Z}_C$, clusters, $\mathbf{v}$, clusters centers, $\mathbf{U}$, partition matrix;

initialization
stage 1. build decentralized networks with GK fuzzy clustering (III-B)
  for Z do
    compute fuzzy partition with C clusters and fuzziness m;
    $\mathbf{v}$, $\mathbf{U}$,
stage 2. extract inner-cluster density structure with MST (III-C)
  for Z do
    $d_{\text{core}} :=$ distance to the $n-th$ neighbor;
    compute mutual reachability graph (12), and derive MST;
stage 3. design fleet configurations with available vehicle-types (IV-B)
  foreach $\mathbf{Z}_i \in \mathbf{Z} = [\mathbf{Z}_1, \mathbf{Z}_2, \ldots, \mathbf{Z}_C]$ **do**
    build configuration solutions **if** *feasible* **then**
      compute clusterCost
    evaluate globalCost;

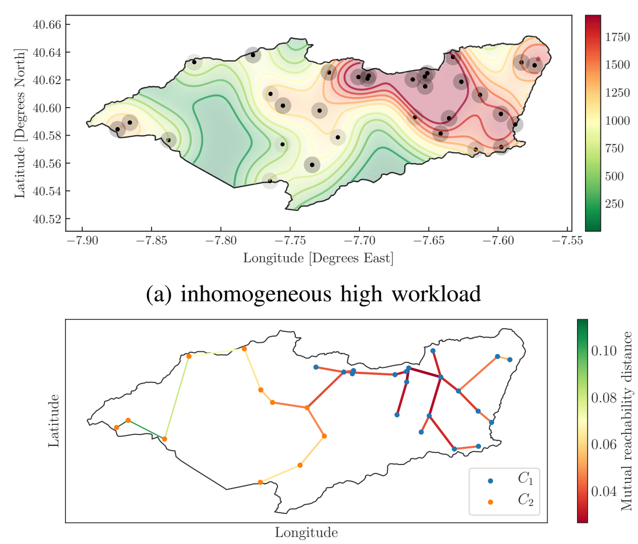
V. Results

This section examines a proposed case-study based on real locations from rural areas in the central region of Portugal, where there is typically increased fire hazard. The demand was modeled as outlined in section II. For assessment of the proposed clustering framework, the scenarios presented in Fig. 4 were tested, though special attention was given to the analysis of a case resembling an active fire monitoring mission (*i.e.*, inhomogeneous with high workload). For this approach to dimensioning and design of multi-UAV fleets, the deployment/land points are not pre-established because in real contexts these can be executed by mobile operational teams, thereby assumed to be within the range of aerial services. In reality, higher demand density for aerial services in fire monitoring scenarios is mainly due to higher risks for populations in wildland-urban interfaces, or because some areas are more susceptible to phenomena of extreme fire behavior.

The stages of the proposed algorithm are illustrated in Fig. 5, for an example of an inhomogeneous high workload case. Observing Fig. 5b representing the GK fuzzy clusters and the global mutual reachability graph, there is an higher density in C_1 in comparison to C_2. This information is clearly valuable to select the vehicles for each fleet.

Considering fire monitoring missions, a positive safety parameter, s, is advisable, to provide the system additional flexibility and redundancy in emergency operation scenarios that are highly dynamic. With the overlap between clusters, the fleets can share resources as the situation develops. For comparison, herein the situations analyzed consider two clusters. Vehicle characteristics were defined generically with energy costs for MR and FW as 1500 and 1000, respectively. The maximum range was set for MR as 4000 and for FW as 8000.

Tables I and II present selected fleet design results, showcasing the influence of varying the degree of overlap, *i.e.* the redundancy in the system, for light and heavy load scenarios, respectively. While cluster C_1 has a low reachability level (Fig. 5b), it has high cardinality, thus a combination of vehicles achieves the best trade-off. In turn, the sparsity in cluster C_2 leads to fleets with mostly fixed-wing drones. Attending to the results in both scenarios, varying the degree of overlap does not evidence particular improvement in light-load cases, but can be beneficial if flexibility is desired. For heavy-load cases, the results demonstrate that increasing redundancy ($m = 1.2$) can create systems that are more efficient, but high fault-tolerance ($m = 1.5$) implies a cost increase.



(a) inhomogeneous high workload

(b) GK clustering and MST of mutual reachability graph

Fig. 5: Example of the proposed framework: (a) demand modeling simulation for fire monitoring scenario; (b) decentralized network with fuzzy partitioning.

TABLE I: Optimization results of selected network models for light-load scenarios (homogeneous case).

Clusters (C)	m	Aerial Vehicles C_1	Cost C_1 (F_1)	Aerial Vehicles C_2	Cost C_2 (F_2)	Global Solution (F_G)
2	1.1	MR(1), FW(2)	20959	MR(0), FW(2)	17432	38391
	1.2	MR(1), FW(2)	20959	MR(0), FW(2)	17432	38391
	1.5	MR(0), FW(2)	17306	MR(0), FW(3)	23809	41115

TABLE II: Optimization results of selected network models for heavy-load scenarios (nonhomogeneous case).

Clusters (C)	m	Aerial Fleet C_1	Cost C_1 (F_1)	Aerial Fleet C_2	Cost C_2 (F_2)	Global Solution (F_G)
2	1.1	MR(1), FW(4)	37872	MR(1), FW(1)	11127	48999
	1.2	MR(1), FW(3)	24554	MR(1), FW(1)	9747	34301
	1.5	MR(1), FW(2)	22794	MR(1), FW(4)	38152	60946

Without loss of generalization, this demand-driven approach can be applied to a multitude of aerial services, by establishing different parameters according to the application requirements.

VI. Conclusion

This paper proposes a framework for decentralized distribution of multi-UAV fleets for on-demand aerial services, addressing strategic and tactical decision-making related to dimensioning and design of aerial networks. The proposed clustering-based approach is threefold: *i)* it derives decentralized networked systems using fuzzy clustering to ensure adequate area coverage in the region of interest; *ii)* within each cluster, inner-clusters based on hierarchical density structure are extracted to dimension the multi-UAV systems with adequate vehicle-types; *iii)* fleet configurations are designed with the required number of UAVs to meet the demand. The overarching benefit of handling data uncertainty using a soft clustering approach is that it results in increasing the flexibility and fault-tolerance of the networked system.

Following this dimensioning and design strategy, to delve into actual operationalization of fleet management, multi-UAV mission planning can be framed into well-conditioned resource allocation and scheduling problems. The proposed method with fuzzy boundaries opens opportunities to research cooperative strategies, *e.g.* to balance workload between neighboring regions. Future formulations of the mission planning of multi-UAV fleets shall also evolve to include different priority levels and time-windows constraints, to approximate the study scenarios to decision-making problems faced in real contexts.

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