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

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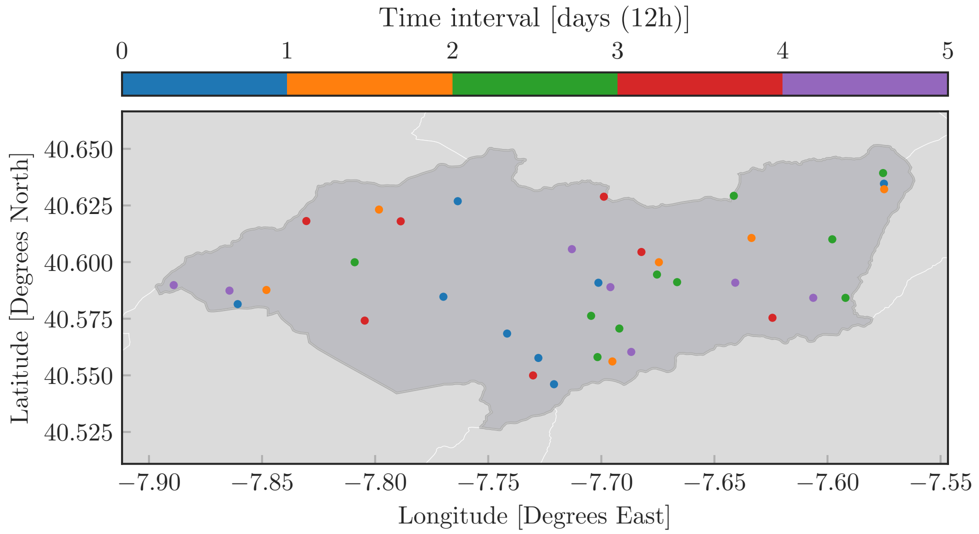
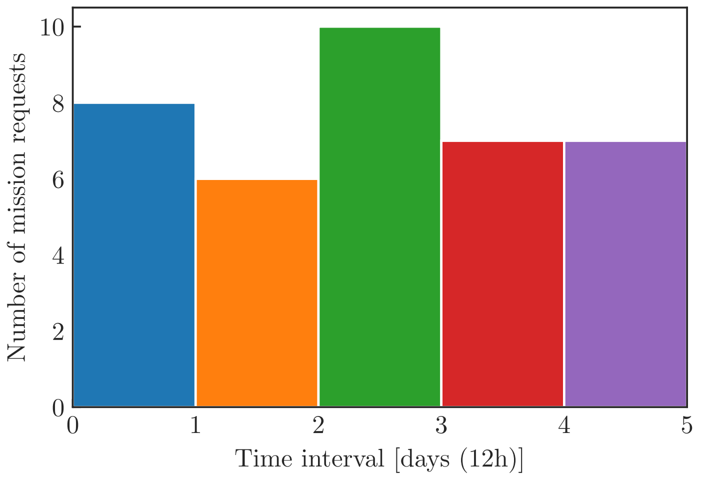
Outline

Context

Unmanned aerial vehicles (UAVs) provide a flexible solution for civilian applications, e.g. last-mile delivery, environmental monitoring or emergency response.

UAV fleets can perform on-demand missions to attend to aerial services requests that are sparsely distributed over a geographical region.





Background

The deployment of multi-UAV fleets to perform aerial services requires a chain of decisions on different levels and temporal scales:

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;

Tactical level mid-term planning decisions regarding **network configurations** for different demand scenarios and deployment strategies, targeting availability and costs;

Operational level short-term operational decisions concerning vehicle routing, scheduling strategies and trajectory optimization for mission-oriented performance.

Problem
Dimensioning and Design of Multi-UAV Fleets

Challenges

- UAVs have stringent energy constraints, thus flights have a limited range
- demand characteristics and variations influences system performance

Proposed Approach

- build decentralized networked systems using clustering-based fuzzy partitioning
- derive density structure to dimension the multi-UAV systems with adequate vehicle-types
- design fleet configurations with the required UAVs to satisfy demand

Demand Modeling

- The demand of aerial services can be modeled as a stochastic process describing a **spatiotemporal** pattern using **Poisson point processes**.

- The requests are defined 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**.

- The temporal uncertainty of the demand is described by the variability in the interval of time between consecutive requests, which follows a **continuous decaying exponential distribution**.

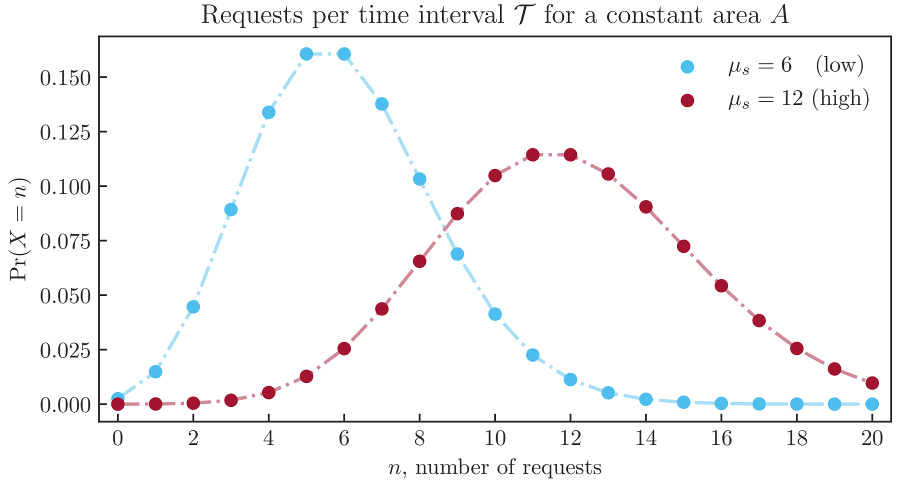
Demand Modeling
Load Level

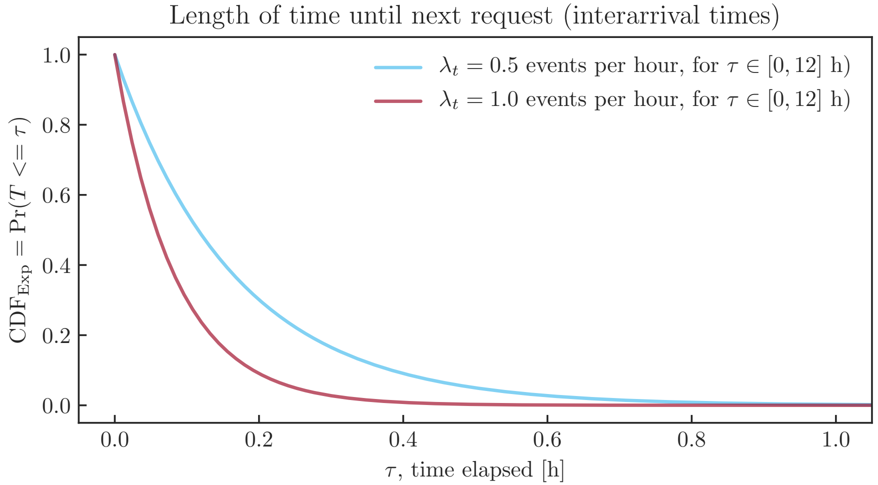
To establish different load levels, high and low workload scenarios are modeled by selecting distinct spatial and temporal intensities.

The process will be considered stationary, i.e. the average spatial and temporal intensities do not vary throughout the time-horizon.

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

Interarrival times $$\left[F_{\text{Exp}}(\tau; \mu_t)\right]^{-1} = -\frac{ln(1-\tau)}{\mu_t} = T$$

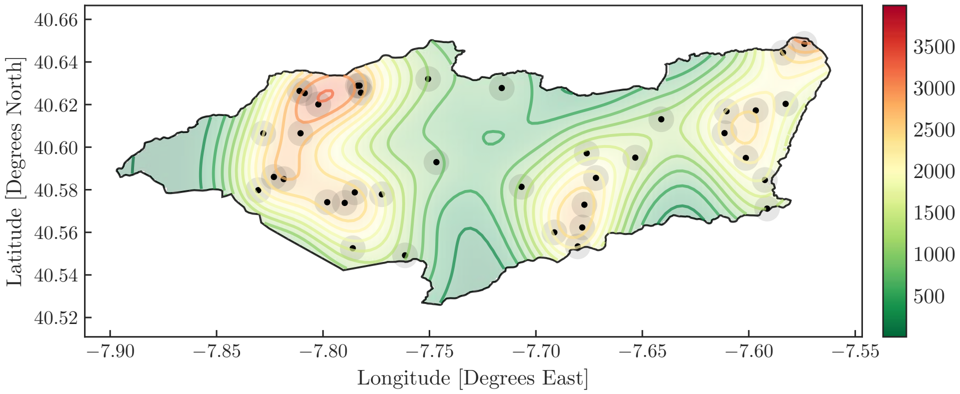




Demand Modeling
Process Type

For the **homogeneous case**, the spatial coordinates (x, y) are generated by a uniform distribution within the limits of the specified bounded area A.

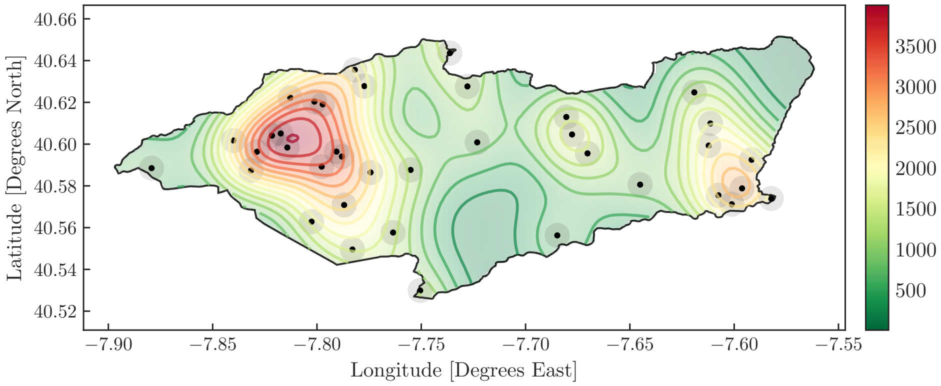
Demand Density represented using Kernel Distribution Estimation (KDE)



For the **nonhomogeneous case**, the spatial coordinates can be generated by a spatially varying deterministic intensity function $\Lambda(x, y)$, where points are eliminated or retained according to a probability which depends on spatial location:

$$\Lambda(x, y) = 2(x^2 + y^2)$$

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

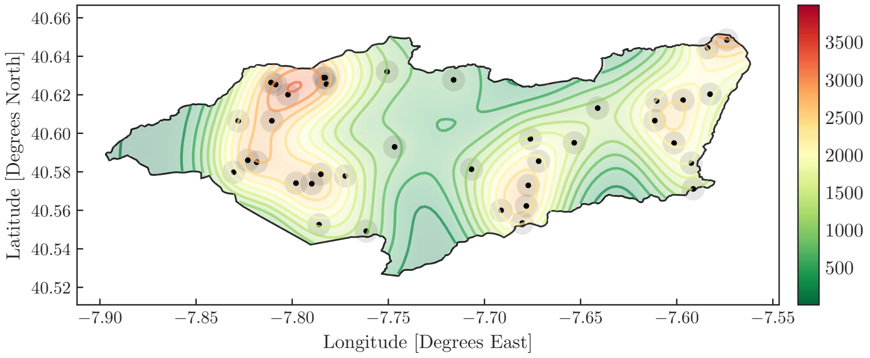


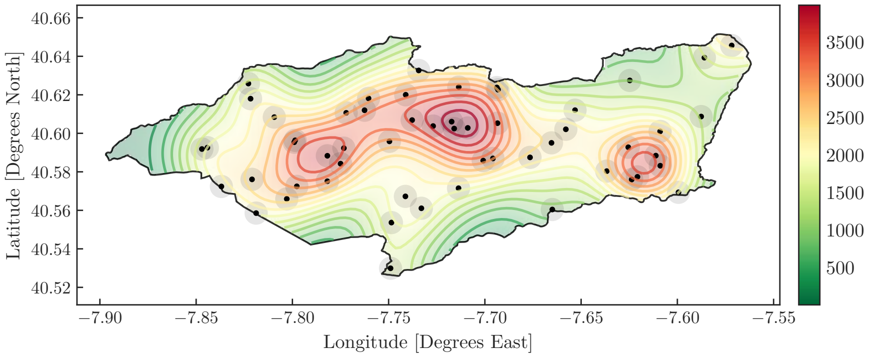
Demand Modeling
Scenarios

By using distinct load levels, high and low workload scenarios can be modelled for both homogeneous and nonhomogeneous processes.

Light Load Level | **Heavy Load Level**

H





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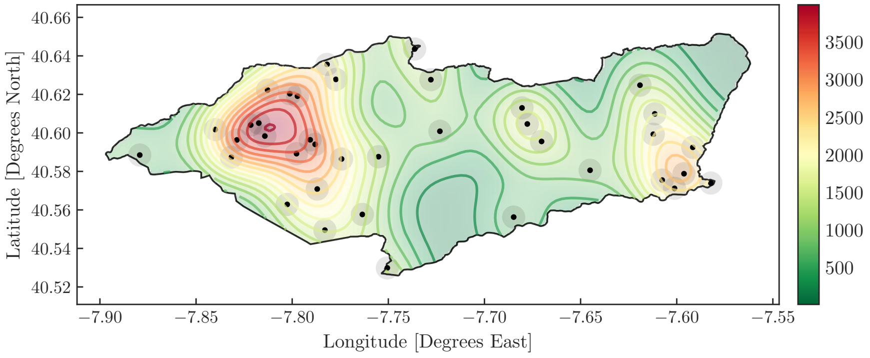
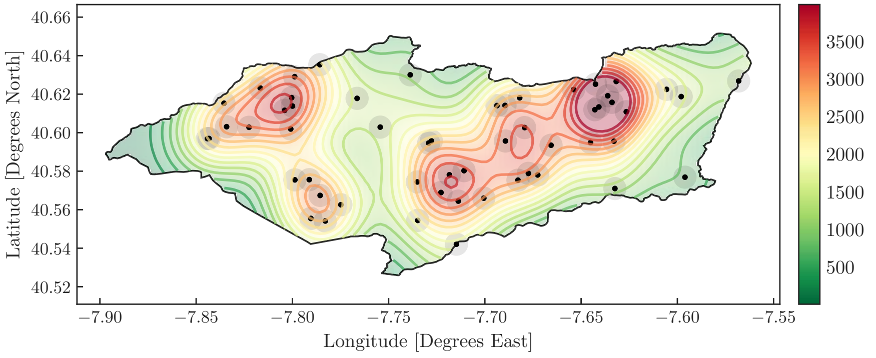




Clustering-based graph Partitioning

- The problem of deploying UAVs to perform surveillance or monitoring tasks over extensive areas with a high number of aerial services can become a very complex resource allocation problem.
- Due to the energy constraints of aerial platforms, many solutions are unfeasible.
- 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.

Decentralized Fuzzy Approach Advantages

improved flexibility **reduced computational burden** **increased fault-tolerance**

Graph Model

To build decentralized networks of multi-UAV fleets the **demand** is represented through graphs:

- Global network model – *supergraph*
- Decentralized network model – *subgraphs*

Demand dataset

- Based on the spatiotemporal demand models presented, the **locations of aerial service requests** in LLA (Latitude, Longitude, Altitude) referential are converted to cartesian space (X, Y, Z) in the NED (North, East, Down) coordinate system.
- **Demand density**, $\hat{\lambda}$, at each location is estimated using Kernel Density Estimation.

Given N samples:

$$\mathbf{Z} = [\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_N] \quad \text{with} \quad \mathbf{z}_k = [X, Y, Z, \hat{\lambda}]^T$$

Demand-driven Clustering

Objective

Combine spatial and intensity measures to represent demand characteristics

Distance measures

- Mahalanobis distance – adaptive squared inner norm for fuzzy clustering
- Core distance – based on Eucledian distance to the *n-th* neighbor

Demand Density Estimates

- Kernel Density Estimate (KDE) – translates the number of missions per area
- Mutual Reachability Distance (MRD) – conveys the proximity of nearby missions

Demand-driven Clustering for Multi-UAV Networks Algorithm

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 coordinates and KDE density estimate

Stage 1 build decentralized networks with GK fuzzy clustering
for $\mathbf{Z}$ **do**
compute fuzzy partition with *C* clusters and fuzziness *m*;

Stage 2 extract inner-cluster density structure with MST
for $\mathbf{Z}$ **do**
$d_{\text{core}} :=$ distance to the *n-th* neighbor;
compute mutual reachability graph and derive MST

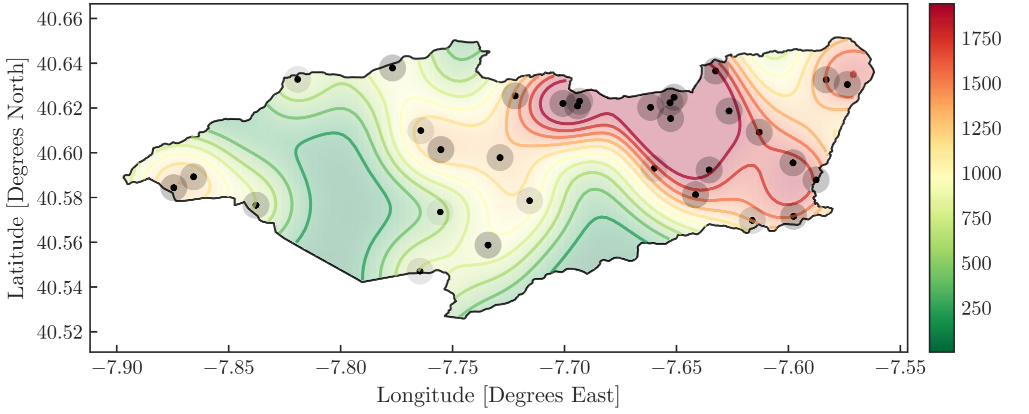
Stage 3 design fleet configurations with available vehicle-types
foreach $\mathbf{Z}_i \in \mathbf{Z} = [\mathbf{Z}_1, \mathbf{Z}_2, \ldots, \mathbf{Z}_C]$ **do**
build configuration solutions **if** feasible **then**
compute clusterCost;
evaluate globalCost;

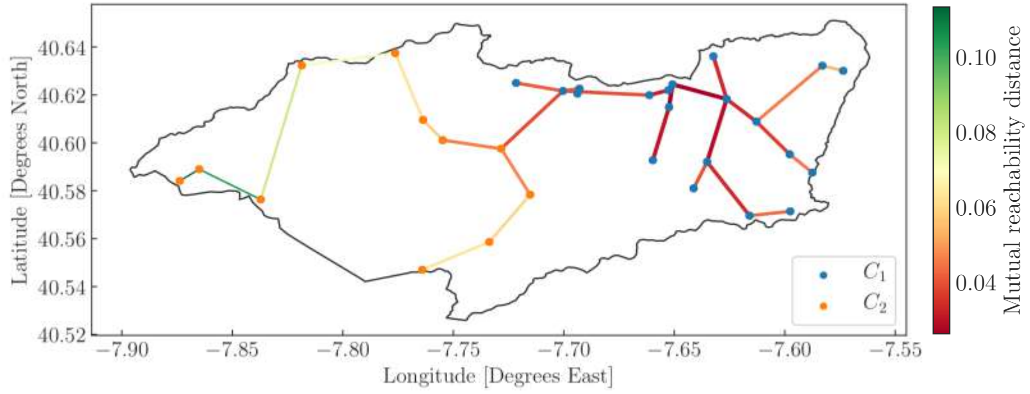
Results

Experiments were performed for a case-study based on real locations from **rural areas** in the central region of Portugal, where there is typically increased fire hazard.

Special attention was given to the analysis of a case resembling an **active fire monitoring** mission (i.e., inhomogeneous with high workload)

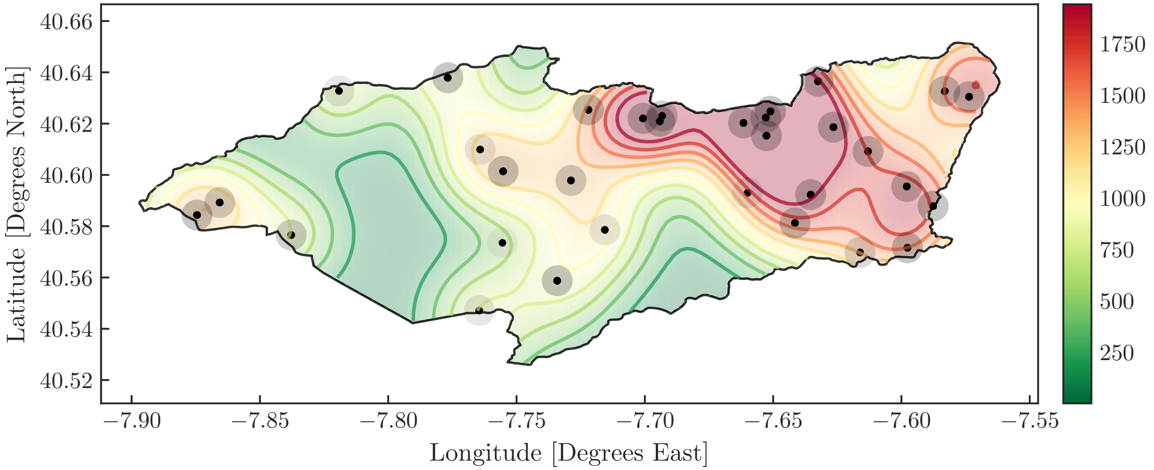
- Fuzzy Gustafson-Kessel Clustering Algorithm partitions the total workload into two fleets;
- Mutual Reachability Distance clearly distinguishes areas with higher concentration of services, which informs vehicle selection.





Results

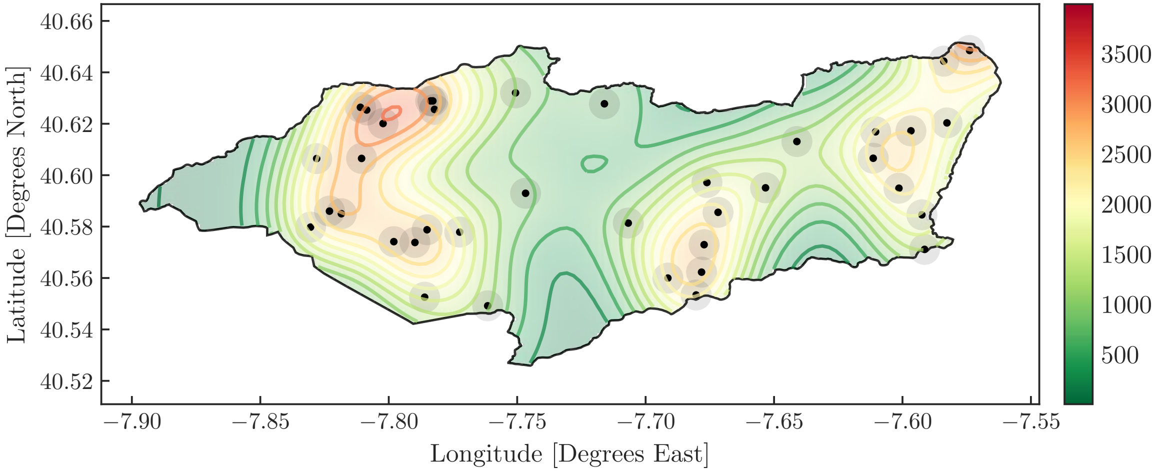
Heavy-Load Scenarios (non-homogeneous case)						
Clusters C	overlap m	Aerial Vehicles, C_1	Cost C_1	Aerial Vehicles, C_2	Cost C_2	Global Cost
2	1.1	MR(1), FW(4)	37872	MR(1), FW(1)	11127	48999
	1.2	MR(1), FW(3)	24554	MR(1), FW(1)	9747	**34301**
	1.5	MR(1), FW(2)	22794	MR(1), FW(4)	38152	**60946**



- increasing redundancy enables a more efficient system cost-wise
- higher fault-tolerance implies a significant cost increase in non-homogeneous case for heavy-load scenarios.

Results

Light-Load Scenarios (homogeneous case)						
Clusters C	overlap m	Aerial Vehicles, C_1	Cost C_1	Aerial Vehicles, C_2	Cost C_2	Global Cost
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**



- varying the degree of overlap does not provide particular improvement in light-load cases cost-wise;
- can be beneficial if flexibility and improved fault-tolerance is desired

Results

Light-Load Scenarios (homogeneous case)						
Clusters C	overlap m	Aerial Vehicles, C_1	Cost C_1	Aerial Vehicles, C_2	Cost C_2	Global Cost
2	1.1	MR(1), FW(2)	20959	MR(0), FW(2)	17432	38391
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Heavy-Load Scenarios (non-homogeneous case)						
Clusters C	overlap m	Aerial Vehicles, C_1	Cost C_1	Aerial Vehicles, C_2	Cost C_2	Global Cost
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**

Conclusion

Highlights

- decentralized approach takes into account vehicle characteristics and energy constraints;
- by dimensioning the problem using a demand-driven approach, the design and deployment problems become simpler to address;
- using fuzzy boundaries as a design strategy enables the application of cooperative resource allocation frameworks;

Future Work

- introduce dynamic intensity levels in demand modeling, and include time-windows and priority levels for the tasks;
- develop frameworks for cooperation between neighboring fleets.

Questions

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To know more about this research check out the Eye in the Sky project @ adai.pt/eyeinthesky

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