A Distributed Pareto-based Path Planning Algorithm for Autonomous Unmanned Aerial Vehicles (Extended Abstract) *

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Abstract

Autonomous Unmanned Aerial Vehicles (UAVs) are in increasing demand thanks to their applicability in a wide range of domains. However, to fully exploit such potential, UAVs should be capable of intelligently planning their collision-free paths as that impacts greatly the execution quality of their applications. While being a problem well-addressed in literature, most presented solutions are either computationally complex centralised approaches or ones not suitable for the multiobjective requirements of most UAV use-cases. This extended abstract introduces ongoing research on a novel distributed Pareto path planning algorithm incorporating a dynamic multi-criteria decision matrix allowing each UAV to plan its collision-free path relying on local knowledge gained via digital stigmergy. The article presents some initial simulations results of a distributed UAV Traffic Management system (UTM) on a weighted multilayer network.

1 Introduction

With the miniaturisation of low energy consumption sensors, the recent introduction of 5G and the wide adoption of Internet of Things (IoT), the autonomous mobile robotics industry and specifically the UAV industry is set to register some of its highest Compound Annual Growth Rates (CAGR) for the coming decade. The demand for autonomous UAVs is increasing enormously, owing to their flexible operational potential in a wide array of applications that were previously deemed infeasible. Some predominant examples in literature include logistics [Fernández-Caramés *et al.*, 2019], monitoring, surveillance and disaster management [Feng *et al.*, 2015]. Nevertheless, to fully exploit such potential let alone safely manage UAV traffic, autonomous UAVs should be capable of intelligently and safely navigating their dynamic environments since in majority of scenarios, how well they plan their paths impacts greatly the execution quality their application.

Mobile robot path planning is an optimisation problem that has been well-addressed in the literature over the past years. However, most of the approaches have mainly focused on 2-dimensional (2D) and 2.5-dimensional (2.5D) methods [Yang *et al.*, 2016] which are suitable for ground or water surface mobile robots, while approaches for UAVs and other highly mobile autonomous robots requiring 3-dimensional (3D) path planning, remain less explored. As mobile robot path planning is proven to be NP-hard, 3D path planning is also NP-hard with an additional dimension, altitude [Yang *et al.*, 2016]. In the recent years, several methods were proposed in the literature to address this challenging problem. Yang et al. in [Yang *et al.*, 2014] analyse and categorise some of the main 3D path planning algorithms. Some predominant examples building on classical approaches include the anytime heuristic search algorithm [Likhachev *et al.*, 2004], an Anytime Dynamic A* [Likhachev *et al.*, 2005] and Lazy Theta* [Nash *et al.*, 2010]. While the aforementioned algorithms can find optimal paths through decomposing networks, they typically optimise the path efficiency for one objective which makes them less suitable for applications in complex environments [Jun and Qingbao, 2010].

To address this, research turns to multiobjective optimisation approaches which call for solutions that account for multiple cost criteria, where optimising one criterion may be at the cost of another. The complexity of such problems significantly increases with the number of objectives to be optimised, hence researchers' often shift to approximate methods to obtain good quality solutions in reasonable time. Broadly, approximate methods can be classified under four main categories namely, scalar approaches, criterion-based approaches, indicator-based approaches and dominance-based approaches [Talbi, 2009].
Such methods have been investigated in the literature for decades with predominant examples of bio-inspired search paradigms like the non-dominated sorting genetic algorithm (NSGA)[Srinivas and Deb, 1994] and variations of NSGA-II [Deb *et al.*, 2000] and NSGA-III [Deb and Jain, 2014] for different environmental models, robot types and applications. The main drawback, however, of using evolutionary algorithms for path planning is computational complexity making them more fit for offline centralised approaches than distributed online path planning in autonomous mobile robots.

In the context of UAV dynamic online path planning, the

*This article is an extended abstract of an on going work entitled *A Distributed Pareto Path Planning Algorithm for Autonomous Mobile Robots*.

majority of presented solutions either address a single optimisation objective or the multiobjective optimisation problem with centralised approaches. Such approaches will eventually face the inherent limitations of centralised systems when it comes to scalability and resilience of UAV applications and UAV Traffic Management. To this end, this article presents our work in progress and outlines a novel distributed Pareto-based path planning algorithm for autonomous UAVs. The proposed algorithm incorporates an initial path planner complemented by a dynamic online multiobjective path planner extending the Local Pheromone Guided (LPG) A* heuristic presented in [S. Labib *et al.*, 2019] allowing individual UAVs to compute a non-dominated set of paths at every individual search step, i.e. when facing traffic congestion, and rely on dynamically updated multi-criteria decision matrix to select a solution autonomously.

The remainder of this article is as follows. Section 2 outlines an operational example of a distributed UAV Traffic Management system relying on the proposed multilayer model of the Class G airspace initially presented in [S. Labib *et al.*, 2019] followed by an initial optimisation problem formulation. Section 3 outlines the proposed technical approach followed by initial validation results in Section 4. Finally Section 5 concludes and presents the next steps and future work.

2 Use Case: UAV Traffic Management

To validate the path planning algorithm, this section narrates an operational example of a distributed UAV Traffic Management (UTM) system relying on the proposed multilayer model of the Class G airspace initially presented in [S. Labib *et al.*, 2019] (see Figure 1).

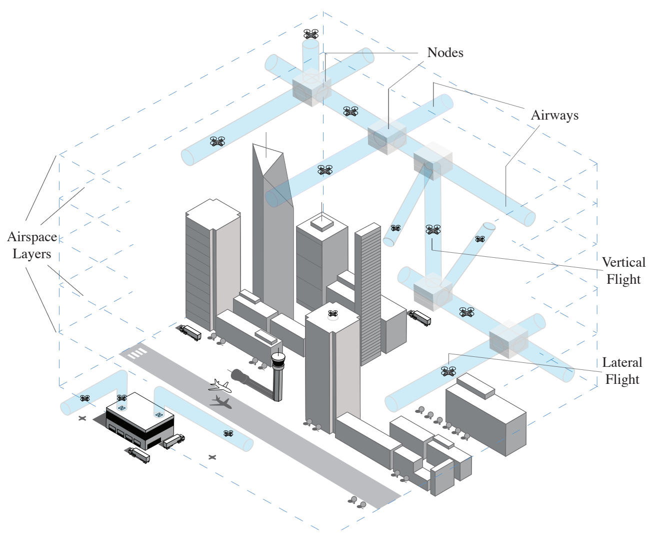


Figure 1: Multilayer model of the low-altitude airspace.

The use case illustrates an operational scenario where a group of multi-rotor autonomous UAVs are deployed on a collective monitoring mission similar to that presented in [Feng *et al.*, 2015]. UAVs are considered to have different individual roles in the mission, hence having priorities and incentives to get to their destination. The UAVs enter the *airspace* through different *nodes* and traverse from origin to destination along *paths* at different layers. Each altitude segment, referred to as layer, allows different velocity ranges that increase at higher altitude layers. We assume that higher altitudes offer shorter travel times at the cost of higher energy consumption. This assumption is supported by the work presented in [Cho and Yoon, 2018] where higher altitude layers are less cluttered with static obstacles in comparison to lower ones. This will in turn allow UAVs to fly at higher lateral velocities and consume more energy as explained in [Hwang *et al.*, 2018]. As each UAV traverses the network, and precisely at network *nodes*, it communicates and exchanges information (*awareness messages*) with other UAVs within its communication range as explained in our previous work [Labib *et al.*, 2019]. Based on the exchanged rules and traffic information such as traffic density and flight velocities, UAVs make local path planning decisions. In turn, switch between *airways*, airspace layers and *flight modes*, namely, lateral, vertical and hover, according to their current battery status and percentage of mission completion (see Figure 2) while trying to minimise both their time of flight and energy consumption.

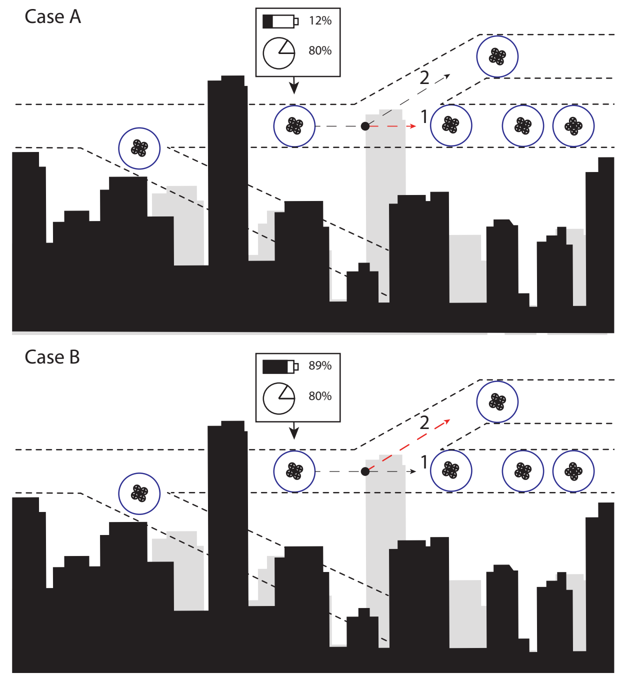


Figure 2: Illustrative scenario. Case A: UAV remains at lower layer path 1 to conserve battery; Case B: UAV opts to higher layer path 2 to avoid congestion.

2.1 UAV Traffic Optimisation and Deconfliction

In alignment with the aforementioned use case, this subsection presents the corresponding formulation of the bi-objective optimisation problem of minimising the total travel time and energy consumption of UAV traffic in the network. Based on our weighted multilayer network description [Labib *et al.*, 2019], the bi-objective function F we aim to optimise can be expressed as:

$$\min \; F = (f_1, f_2) \tag{1}$$

$$f_1 = T = \sum_{i=1}^{I} \sum_{l=1}^{L} a_{il} * t_l \tag{2}$$

$$f_2 = E = \sum_{i=1}^{I} \sum_{l=1}^{L} a_{il} * e_l \tag{3}$$

$$\text{s.t.} \; \sum_{i=1}^{I} a_{il} = c_l, \; l = 1, \ldots, L, \tag{4}$$

$$c_l \leq c_l^{max}, \; l = 1, \ldots, L, \tag{5}$$

$$a_{il} \in \{0, 1\}, \; i = 1, \ldots, I, \; l = 1, \ldots, L, \tag{6}$$

$$E, T \in \mathbb{N}, \tag{7}$$

$$e_l, t_l, c_l \in \mathbb{N}, \; l = 1, \ldots, L, \tag{8}$$

where:

F – bi-objective function (f_1, f_2),

T – objective function (time elapsed),

E – objective function (energy consumed),

I – number of UAVs,

i – index for UAVs,

L – number of airways,

l – index for airways,

a – selection indicator for airways / UAVs $(\in 0, 1)$,

e – energy consumption component for airways,

t – time elapse component for airways,

c – traffic capacity for airways,

c^{max} – maximum traffic capacity for airways.

In the proposed model, each airway in a path has a critical traffic capacity of UAVs that it can traverse; in addition to an allowable maximum velocity which is expressed in terms of time *t* and energy *e*. Therefore, for a number of UAVs *I* over a complete path our first utility function (1) addresses our first objective, minimising the total energy consumption while (2) addresses our second objective which is minimising the total travel time. Complementing this approach, is the deconfliction process. Conflict management is the process of ensuring that UAVs do not collide, we achieve this by following a *strategic* then *tactical* approach (c.f. Table 1). The process is divided into three levels where the aim of each is to reduce the need to apply the proceeding level. Starting with strategic traffic density management in the mission planning phase, signified in *equation 5*, following through with the dynamic tactical level of maintaining separation and finally evasive manoeuvres.

3 Multilayer Multiobjective Path Planning

This section outlines the two stages of the approach followed through the work. The first stage, completed and detailed in [Labib *et al.*, 2019], presented three devised heuristics, namely Global Offline Static heuristic (GOS), Global Probabilistic Dynamic heuristic (GPD) and the Local Pheromone Guided heuristic (LPG). The aim of the first stage was to assess the performance of a completely distributed traffic management system in comparison to a centralised one. The ongoing second stage builds on the first stage's LPG with the main goal of extending the proposed approach to consider multiple optimisation objectives and rely a dynamic multi-criteria decision making approach to allow UAVs to autonomously select a solution based on their current status and local knowledge.

Table 1: Different deconfliction levels.

Conflict Management	
Strategic	I. Mission Planning - Traffic density management
Tactical	II. Remaining Clear - Maintaining separation III. Collision Avoidance - Evasive manoeuvres

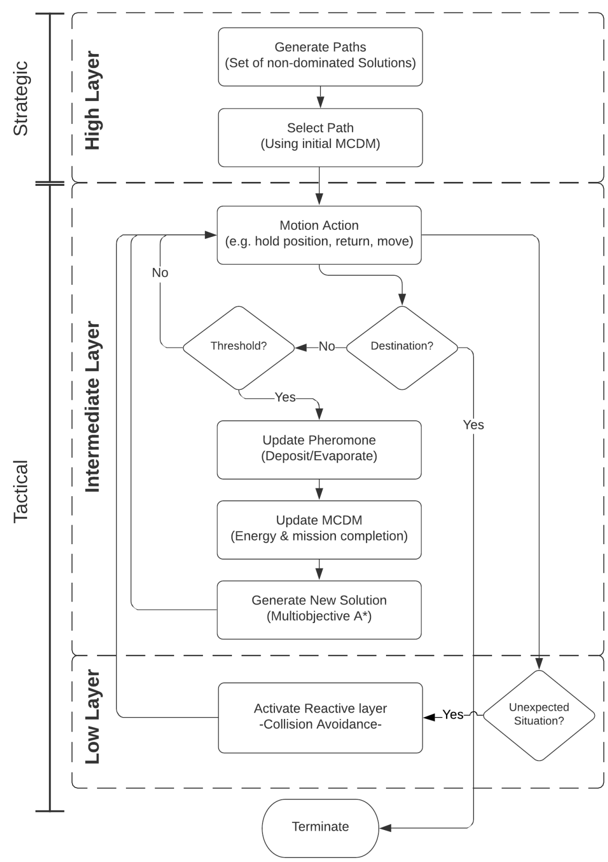


Figure 3: Simplified algorithm flowchart.

The distributed Pareto-based path planning algorithm (D3P), presented in this study builds on the multiobjective A* search algorithm proposed in [Mandow *et al.*, 2005] and detailed in [Mandow and De La Cruz, 2008]. The algorithm is effectively the classical search algorithm with the key modification of computing the Pareto front of the cost criteria instead of summing them, hence the name *Pareto_A**.

Figure 3 illustrates a simplified flowchart of the proposed algorithm divided into a higher proactive layer, a responsive dynamic intermediate layer and a reactive lower layer.

Heuristic 1 : Distributed Pareto-based Path Planning (D3P)

Data: network, weights (t, e, c), start, destination (dest), traffic_threshold (T_{lim}), criteria_matrix

```
1 while UAV not at dest do
2     compute set of solution_paths              ▷ using Pareto_A*
      select best_path                           ▷ using criteria_matrix
      take next_move from best_path
      if c_l ≤ T_lim then
3         set current to next_move               ▷ UAV move
          update t_l, e_l, c_l
4     else
5         compute solution_paths to dest         ▷ using Pareto_A*
          update criteria_matrix                 ▷ dAHP
          select best_path                       ▷ using criteria_matrix
          set current to next_move               ▷ UAV move
          update t_l, e_l, c_l
          update pheromone τ
6     end
7 end
```

Knowing their destination, UAVs generate a set of solutions/paths using *Pareto_A** then relying on their multi-criteria decision matrix, each UAV selects one of the generated paths to follow. UAVs start following the selected shortest path until the traffic on the next airway is superior to a predefined threshold defined by T_{lim}, that is, when c_l = T_{lim} where T_{lim} ¡ c_l^{max} (cf. lines *1–4* in Heuristic 1). In reality, T_{lim} would correspond to the critical traffic density explained in traffic theory as the capacity after which traffic flow becomes congested. At that stage each UAV lays down a pheromone trail τ, where $\tau_l = 1/c_l^{max}$ of airway l. The deposited trail of pheromone acts as a repellent to other UAVs, hence making the airway less desirable to take. In the devised model, intersecting nodes act as decision points at which the following UAVs receive the updated pheromone level and use it to estimate an update of corresponding airways' weights in order to locally compute new alternative paths to their destination (cf. lines *4–6* in Heuristic 1). At this stage, in place of the probabilistic state transition rule used in [Labib *et al.*, 2019], here UAVs rely on a dynamic analytical hierarchy process (dAHP) to make their selection between the generated set of solution from the Pareto-based approach. While dAHP applies the same methodology of the classical Analytical Hierarchy Process (AHP) [Saaty, 1988], it considers the AHP *criteria* and *alternatives* as temporary variables instead of and therefore provides autonomous UAVs a logical framework to determine the cost of each alternative at a given step. In other words, as UAVs traverse the network, alternatives present the different solutions/paths at every decision step where the criteria at that step vary with the state of each UAV. As an initial stage, we consider the energy criterion weight to vary with the level of consumption as guided by $c_i^p = c_0^p \cdot e^{k \cdot p_i}$ where c_i^p is the energy criterion weight at step i, c_0^p is the initial weight of the criterion, k a growth constant and p_i represents the battery consumption level. Hence, the more energy UAVs consume the greater the impact of energy conservation would be on their decision between alternatives.

4 Simulations and Initial Results

This section outlines our experimental setup and presents a snapshot of the first stage of simulation results, detailed in [Labib *et al.*, 2019], corresponding to the first stage in the optimisation approach presented in section 3.

Table 2: Experiment parameters.

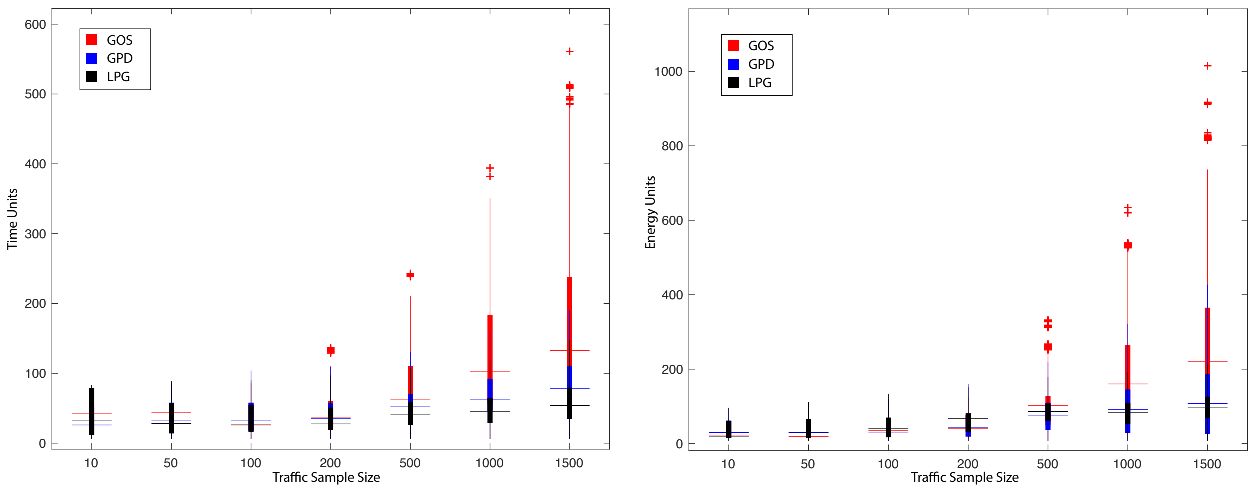
Parameter	**Value**
Number of UAVs (hundreds)	0.1, 0.5, 1, 2, 5, 10, 15
Number of nodes	100 per layer
Number of layers	3
Edge creation probability	20%
Interlayer energy weight interval	[15,20]
Intralayer energy weight intervals	[5,10],[15,20],[25,30]
Interlayer time weight interval	[1,5]
Intralayer time weight intervals	[25,30],[15,20],[5,10]
Interlayer capacity weight interval	50
Intralayer capacity weight interval	[1,5]
GPD decision probability $(p_{reroute})$	100%
LPG T_{lim} percentage of c_l^{max}	50%

For the first stage, experiments are conducted on a three layer network based on the Erdős – Rényi model using Python's NetworkX library and the multiNetX package. Each layer contains the same number of nodes and each airway (intra and inter network) is assigned three weights, *t*, *e* and *c*, uniformly at random in predefined intervals. A single network with a total of 300 nodes and 3 layers (100 nodes per layer) has been used. Between every pair of nodes, there is a 20% probability an edge is created. Table 2 describes the parameters used at this stage of experiments. As a first stage of validation, the experiment is run with the aim of studying the performance of the three heuristics GOS, GPD, LPG with a single optimisation objective in a more realistic scenario to address some of the assumptions made in the previous work in the literature [S. Labib *et al.*, 2019]. Here each UAV has a different origin and destination pair as well as one of the two minimisation objectives.

Figures 4(a) and 4(b) as well as Table 3 present the obtained results when comparing the impact the three heuristics (GOS, GPD, LPG) have on traffic performance in a more realistic scenario.

Figures 4(a)–4(b) present the impact in traffic performance by indicating the median, 25^{th} and 75^{th} percentile, while Table 3 presents the mean and standard deviation in the results after 30 runs of the probabilistic heuristics for every varied parameter over all traffic samples: for every T_{lim} in LPG and for every $p_{rerouting}$ in GPD. It can be observed that, with the exception for traffic sample 10, LPG results show improvement in total UAVs' travel time for all traffic samples.

On the other hand, it is worth to mention that due to the selected parameters and the nature of GPD, encouraging UAVs



(a) Time (b) Energy

Figure 4: (a) Comparison of total UAVs' travel time. (b) Comparison of total UAVs' energy consumption.

Table 3: Comparison of traffic performance using GOS, GPD and LPG.

Traffic	**Heuristic**	**Time** Mean $_{SD}$	**Energy** Mean $_{SD}$	**Path Changes** Mean $_{SD}$	**Layer Changes** Mean $_{SD}$	**Queue Counts** Mean $_{SD}$
10	GOS	**36.6**$_{24.8}$	**33.2**$_{22.8}$	**0**$_{0}$	**16**$_{0}$	**0**$_{0}$
	GPD	37.0$_{27.3}$	37.5$_{25.5}$	**0**$_{0}$	17.9$_{7.0}$	**0**$_{0}$
	LPG	41.5$_{28.8}$	34.6$_{24.9}$	**0**$_{0}$	15.5$_{5.1}$	**0**$_{0}$
50	GOS	42.5$_{24.7}$	**36.1**$_{25.3}$	**0**$_{0}$	**80**$_{0}$	**0**$_{0}$
	GPD	40.1$_{27.1}$	38.1$_{26.8}$	0.2$_{0.6}$	84.6$_{12.8}$	**0**$_{0}$
	LPG	**38.6**$_{26.8}$	39.7$_{27.1}$	1.3$_{1.4}$	92$_{12.4}$	**0**$_{0}$
100	GOS	38.9$_{25.9}$	42.8$_{27.8}$	**0**$_{0}$	196$_{0}$	0$_{0}$
	GPD	40.6$_{26.0}$	**40.9**$_{28.4}$	2.1$_{1.7}$	**175.7**$_{13.8}$	0.2$_{0.5}$
	LPG	**36.1**$_{24.3}$	47.8$_{29.9}$	13.6$_{4.9}$	228.7$_{8.9}$	**0**$_{0}$
200	GOS	46.8$_{31.4}$	52.4$_{35.3}$	**0**$_{0}$	**360**$_{0}$	17$_{0}$
	GPD	41.5$_{25.6}$	**51.0**$_{32.7}$	27.8$_{4.5}$	420.6$_{15.5}$	4.8$_{2.5}$
	LPG	**34.8**$_{21.4}$	59.7$_{31.6}$	63.2$_{6.8}$	585.1$_{16.4}$	**0**$_{0}$
500	GOS	80.4$_{53.4}$	109.6$_{73.9}$	**0**$_{0}$	**864**$_{0}$	300$_{0}$
	GPD	54.5$_{32.6}$	**82.0**$_{59.5}$	258.3$_{20.2}$	1275$_{38.1}$	101.4$_{10.9}$
	LPG	**45.7**$_{25.4}$	84.8$_{41.1}$	331$_{24.9}$	1895.5$_{49.8}$	**1.1**$_{1.2}$
1000	GOS	123.0$_{84.9}$	189.1$_{131.8}$	**0**$_{0}$	**1668**$_{0}$	1372$_{0}$
	GPD	76.1$_{50.3}$	111.649$_{101.3}$	982.4$_{40.8}$	2425.9$_{54.9}$	441.5$_{25.9}$
	LPG	**49.9**$_{27.2}$	**82.8**$_{42.8}$	670.5$_{33.1}$	3592.3$_{57.9}$	**10.4**$_{4.3}$
1500	GOS	162.3$_{114.5}$	264.7$_{193.2}$	**0**$_{0}$	**2584**$_{0}$	3097$_{0}$
	GPD	93.4$_{69.1}$	137.7$_{142.2}$	2267.9$_{81.1}$	3400.9$_{75.7}$	1059.0$_{66.9}$
	LPG	**59.9**$_{34.9}$	**100.8**$_{53.3}$	1220.5$_{52.8}$	6051.5$_{96.5}$	**11.8**$_{4.5}$

to be more inclined to reduce layer changes, these led to a significant difference in reduction of energy consumption in comparison to LPG for traffic samples 50-200. However, what is of greater interest are the results obtained for the larger traffic samples, which are more decisive in the devised scenario, LPG outperforms GPD with significant difference across 4 of the 5 main parameters of comparison, with the exception of the total number of layer changes, which can be explained by the nature of the heuristic LPG which encourages UAVs to explore vertical airways between layers as they offer a higher c_l^{max}. Statistical confidence in our comparisons is assessed by performing the Wilcoxon test [Wilcoxon, 1992]. The overall best result per comparison parameter is shown in bold. Additionally, the dark grey background emphasises the best results that showed statistically significant difference with a 95% confidence.

5 Conclusion and future work

The recent developments in technologies has surged the demand for autonomous mobile robots and specifically UAVs. Nevertheless, for such autonomous UAV systems to be utilised to their fullest potential, UAVs have to be capable of safely and intelligently planning their paths.

In this extended abstract, we presented our work in progress and outlined a novel distributed Pareto-based path planning algorithm for autonomous UAVs. The proposed algorithm incorporates an online dynamic multiobjective path planner extending the LPG A* heuristic presented in [S. Labib *et al.*, 2019] allowing individual UAVs to compute a non-dominated set of paths at every search step and rely on a dynamically updated multi-criteria decision matrix to select a solution autonomously.

Whilst the first stage of simulations was run to validate the model by only considering a single optimisation objective, the second stage of simulations to evaluate the Pareto-based approach are currently ongoing. Additionally, a more realistic instance of the airspace is being used for traffic management testing. Moreover, our future work will build on the second stage by incorporating a more realistic communication scenario and investigate the impact of coverage and different protocols on traffic behaviour as well as explore more realistic communication metrics, given the challenging nature of UAV networks.

Acknowledgments

This work is partially funded by the joint research programme UL/SnT–ILNAS on Digital Trust for Smart–ICT.

References

[Cho and Yoon, 2018] Jungwoo Cho and Yoonjin Yoon. Assessing the airspace availability for suav operations in urban environments: A topological approach using keep-in and keep-out geofence. In *2018 International Conference on Research in Air Transportation (ICRAT)*. ICRAT, 2018.

[Deb and Jain, 2014] K. Deb and H. Jain. An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part i: Solving problems with box constraints. *IEEE Transactions on Evolutionary Computation*, 18(4):577–601, Aug 2014.

[Deb *et al.*, 2000] Kalyanmoy Deb, Samir Agrawal, Amrit Pratap, and Tanaka Meyarivan. A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: Nsga-ii. In *International conference on parallel problem solving from nature*, pages 849–858. Springer, 2000.

[Feng *et al.*, 2015] Quanlong Feng, Jiantao Liu, and Jianhua Gong. Uav remote sensing for urban vegetation mapping using random forest and texture analysis. *Remote sensing*, 7(1):1074–1094, 2015.

[Fernández-Caramés *et al.*, 2019] Tiago M. Fernández-Caramés, Oscar Blanco-Novoa, Iván Froiz-Míguez, and Paula Fraga-Lamas. Towards an autonomous industry 4.0 warehouse: A uav and blockchain-based system for inventory and traceability applications in big data-driven supply chain management. *Sensors*, 19(10), 2019.

[Hwang *et al.*, 2018] Myeong-hwan Hwang, Hyun-Rok Cha, and Sung Jung. Practical endurance estimation for minimizing energy consumption of multirotor unmanned aerial vehicles. *Energies*, 11(9):2221, 2018.

[Jun and Qingbao, 2010] H. Jun and Z. Qingbao. Multi-objective mobile robot path planning based on improved genetic algorithm. In *2010 International Conference on Intelligent Computation Technology and Automation*, volume 2, pages 752–756, May 2010.

[Labib *et al.*, 2019] Nader S. Labib, Grégoire Danoy, Jedrzej Musial, Matthias R. Brust, and Pascal Bouvry. Internet of unmanned aerial vehicles—a multilayer low-altitude airspace model for distributed uav traffic management. *Sensors*, 19(21):4779, Nov 2019.

[Likhachev *et al.*, 2004] Maxim Likhachev, Geoffrey J Gordon, and Sebastian Thrun. Ara*: Anytime a* with provable bounds on sub-optimality. In *Advances in neural information processing systems*, pages 767–774, 2004.

[Likhachev *et al.*, 2005] Maxim Likhachev, David I Ferguson, Geoffrey J Gordon, Anthony Stentz, and Sebastian Thrun. Anytime dynamic a*: An anytime, replanning algorithm. In *ICAPS*, volume 5, pages 262–271, 2005.

[Mandow and De La Cruz, 2008] Lawrence Mandow and José. Luis Pérez De La Cruz. Multiobjective a* search with consistent heuristics. *J. ACM*, 57(5), June 2008.

[Mandow *et al.*, 2005] Lawrence Mandow, JL Pérez De la Cruz, et al. A new approach to multiobjective a^* search. In *IJCAI*, volume 8. Citeseer, 2005.

[Nash *et al.*, 2010] Alex Nash, Sven Koenig, and Craig Tovey. Lazy theta*: Any-angle path planning and path length analysis in 3d. In *Twenty-Fourth AAAI Conference on Artificial Intelligence*, 2010.

[S. Labib *et al.*, 2019] N. S. Labib, G. Danoy, J. Musial, M. R. Brust, and P. Bouvry. A Multilayer Low-Altitude Airspace Model for UAV Traffic Management. In *In Proceedings of the 9th ACM Symposium on Design and Analysis of Intelligent Vehicular Networks and Applications DIVANet'19*. ACM, Nov 2019.

[Saaty, 1988] Thomas L Saaty. What is the analytic hierarchy process? In *Mathematical models for decision support*, pages 109–121. Springer, 1988.

[Srinivas and Deb, 1994] Nidamarthi Srinivas and Kalyanmoy Deb. Muiltiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary computation*, 2(3):221–248, 1994.

[Talbi, 2009] El-Ghazali Talbi. *Metaheuristics: from design to implementation*, volume 74. John Wiley & Sons, 2009.

[Wilcoxon, 1992] Frank Wilcoxon. Individual comparisons by ranking methods. In *Breakthroughs in statistics*, pages 196–202. Springer, 1992.

[Yang *et al.*, 2014] Liang Yang, Juntong Qi, Jizhong Xiao, and Xia Yong. A literature review of uav 3d path planning. In *Proceeding of the 11th World Congress on Intelligent Control and Automation*, pages 2376–2381. IEEE, 2014.

[Yang *et al.*, 2016] Liang Yang, Juntong Qi, Dalei Song, Jizhong Xiao, Jianda Han, and Yong Xia. Survey of robot 3d path planning algorithms. *Journal of Control Science and Engineering*, 2016:5, 2016.