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Auction-based Task Allocation for Safe and Energy Efficient UAS Parcel Transportation

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Abstract

In this paper, two greedy auction-based algorithms are proposed for the allocation of heterogeneous tasks to a heterogeneous fleet of UAVs. The tasks set is composed of parcel delivery tasks and charge tasks, the latter to guarantee service persistency. An optimization problem is solved by each agent to determine its bid for each task. When considering delivery tasks, the bidder aims at minimizing the energy consumption, while the minimization of the flight time is adopted for charge tasks bids. The algorithms include a path planner that computes the minimum risk path for each task-UAV bid exploiting a 2D risk map of the operational area, defined in an urban environment. Each solution approach is implemented by means of two auction strategies: single-item and multiple-item. Considerations about complexity and efficiency of the algorithms are drawn from Monte Carlo simulations.

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Keywords: unmanned aerial vehicles; drone delivery; task allocation; auctions; energy optimization; greedy algorithm; risk map; risk-aware path planning;

1. Introduction

The rise of interest in Unmanned Aerial Vehicles (UAVs) has become more and more significant over the last decade. Globally, there are numerous application areas where UAVs are now starting to be used, such as parcel delivery, transportation of medical samples, mapping and surveillance, as discussed by Cohen et al. (2021). The foreseen advantages of the development of aerial logistics are the reduction of road vehicles-related traffic and CO_2

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emissions, the increased diversification of transportation options, the reduction of transit deserts, the rise of new economic opportunities, the optimization of the logistic process itself, the reduction of inventory costs and human resources usage and the process shortening, as pointed out by Škrinjar et al. (2018). Alkouz et al. (2021) proposed a framework of service-oriented architectures for enabling drone delivery services, focusing on service definition, safe aerial highways and robust and efficient UTM (UAS Traffic Manager) infrastructure. Raj et. al (2019) highlighted that, besides the establishment of a well-defined regulatory framework and the adoption of skilled workforce, safe path planning in urban environment is one of the most critical factors for the development of the drone logistic sector, especially if considering public acceptance.

We believe that a safe, efficient, scalable and flexible service-oriented task allocator is needed for the UTM infrastructures of the dense airspace scenarios of the future. Multi-robot task allocation techniques are a promising tool for task assignment in distributed, complex and heterogeneous systems. A comprehensive review and categorization of such techniques based on optimality, scalability, robustness and communication architecture is proposed by Skaltsis et al. (2021), Khamis et al. (2015) and by Poudel and Moh (2022), the latter uniquely focuses on UAS operations. Exact solution approaches are mainly optimization-based and may be combined with heuristic algorithms for scalability with respect to the number of tasks and agents, but lack robustness to communication failures and can't handle dynamic tasks. A Mixed-Integer Linear Programming (MILP) formulation with receding horizon task assignment heuristics is applied to a UAS delivery task allocation problem in Song et. al (2018), considering constraints on flight time, payload capacity and payload effect on flight time. A sequential greedy algorithm solves the MILP formulation for cooperative UAS delivery in Oh et al. (2018). In sub-optimal decentralized approaches, agents assign tasks among themselves according to well-defined communication protocols. Such approaches lead to sub-optimal solutions, while ensuring robustness, scalability, low communication costs, uncertainty and dynamic task management. The auction-based algorithm of Nanjanath and Gini (2008) ensures the handling of dynamic tasks, unexpected obstacles and communication losses or delays by sequentially re-broadcasting the tasks not yet completed, while obtaining near optimal total completion time. A single-item auction algorithm is proposed by Nunes and Gini (2015), where each task has time window constraints and robots' bids result from optimization of each task's completion time and traveled distance. Several auction-based algorithms exist, an exhaustive analysis and comparison under communication losses has been proposed by Otte et al. (2020), indicating the multiple-item auctions as the most promising ones. Farinelli et al. (2017) approached ground vehicles' coordination for a warehouse's logistic scenario with binary graph-based distributed optimization problems. Problem decomposition and hybrid solutions are also widely used to efficiently handle big and complex problems, *i.e.*, with big instances and heterogeneous agents and tasks. Bays et al. (2019) adopted a two-stage MILP and auction-based solution to outperform computational times of exact holistic Service Agent Transport Problem (SATP) solutions.

The task allocation is often combined with path planning, solving the so-called Task and Motion Planning Problem (TAMP) as discussed in Mansouri et al (2021). In Tan et al. (2020) a MILP formulation is combined with the RRT* (Rapidly-exploring Random Tree "star") algorithm, while in Li et al. (2017) a linear programming model is integrated with a path planner based on a genetic algorithm. The optimality of the path planner is an essential feature when solving the TAMP problem because the quality of the solution of the task allocation is strictly dependent on the quality of the computed path.

Another essential aspect to be evaluated with the UAS parcel transportation is public safety. A possible crash of the UAV on the ground in a populated area may involve people and, in the worst case, it may cause casualties. For this reason, several risk-aware path planning algorithms for UAVs have been proposed in the literature, such as in Rudnick-Cohen et al. (2016) and Primatesta et al. (2021). In particular, our previous works in Primatesta et al. (2018) and in Primatesta et al. (2020b) proposed a framework for safe UAS navigation able to compute safe routes for UAS in urban areas. The proposed strategy generates a risk map quantifying the risk of flying over a populated area. Hence, a risk-aware path planning algorithm based on the well-known RRT* minimizes the overall risk and the flight time.

In this paper, we propose two auction-based multiple constraints task assignment algorithms to assign parcel delivery tasks with time constraints and charge tasks in order to address service persistency issues. The proposed solutions include optimization of energy consumption or flight time depending on task type. Moreover, the proposed solution includes the risk-aware path planning strategy proposed in Primatesta et al. (2018) with the aim of computing safe routes to be evaluated by the task allocator.

The paper is organized as follows. In section 2, the scenario of reference is defined as well as the problem formulation and the assumptions. Section 3 presents the methodology behind the proposed auction-based solutions approaches adopted for allocating tasks to a heterogeneous fleet of UAVs, with minimization of energy consumption for delivery tasks, flight time for charge tasks and planning of minimum risk paths. In Section 4, the Monte Carlo simulation results are discussed. For the sake of the evaluation, each solution is implemented by means of two auction strategies: single-item and multiple-item. Conclusions and future works are drawn in Section 5.

Nomenclature

c_d^i	UAV i drag coefficient
m^i	UAV i mass
m_{pj}	Payload mass of delivery task j
g	Gravity acceleration
ρ	Air density
A_d^i	Cross section of UAV i with respect to the direction of motion
A_r^i	Total rotor disk area of UAV i
F_M^i	UAV i Figure of Merit
η	Energy computation efficiency factor
$L_1{}^i_j$	Minimum-risk path length from UAV i position to delivery task j pick-up position
$L_2{}^i_j$	Minimum-risk path length from payload pick-up to delivery positions of task j with UAV i
d^i_j	Distance between UAV i position and charge station j
v^i_j	Velocity of UAV i during task j execution
E^i_{MAX}	Maximum energy stored in the battery of UAV i
BL^i	Battery level of UAV i
BL_T	Threshold battery level of each UAV in the fleet
E^i_{MIN}	UAV minimum energy required to reach a charge station in worst case scenario
E_{TOTAL}	UAVs' total energy required to perform all tasks
T_i^i	First time instant at which UAV i can start executing a task
T_{DDj}	Due date of task j
v^i_{MAX}	Maximum velocity of UAV i
M	Number of UAVs in the fleet
N	Number of parcel delivery tasks
O	Number of charge stations
r	Auction-based algorithm's round
N_{UNSOLD}	Number of unsold delivery tasks in round r of multiple-item auction-based algorithm

2. Problem Statement

We consider the problem of allocating N parcel delivery tasks with a due date constraint T_{DD} to a heterogeneous fleet of M UAVs. Parcel delivery tasks consist of transporting a payload mass m_P, which can vary from one task to the other, from a pick-up location to a delivery location. Each delivery task has its own pick-up and delivery location within an urban area of reference, *i.e.,* the operational area. The goal is to allocate all N tasks minimizing the total energy E_{TOTAL} required by the fleet to execute them, respecting the maximum allowed makespan T_{DD}. Since UAVs have limited battery capacity, charge tasks have also to be allocated in order to guarantee service persistency. Charge tasks are encoded as locations inside the operational area to be visited by the UAVs of the fleet in the shortest possible amount of time, without running out of energy. As soon as a UAV reaches a charge station, the battery is replaced with a fully charged one. The following assumptions are made:

- The payload capacity of a UAV is at most equal to its mass.
- A UAV can't carry multiple payloads at the same time.
- UAVs' velocity remains constant during task execution.

- The completion time of a task is the ratio between the UAV-task assignment-related path length and the velocity of task execution.
- The time required for battery replacement is negligible.
- UAVs can't reach charge stations if they are executing a delivery task.

Considering the aforementioned framework, as the operational area is populated, we also address the problem of planning minimum risk paths for every pair of UAV-task assignments. It is straightforward that the whole problem falls into the category of multi-objective optimization problems in form of heterogeneous task allocation for a multi-agent system.

3. Proposed Method

Allocating a heterogeneous set of tasks to a heterogeneous set of agents is in general a NP-hard problem (nondeterministic polynomial time problem hard at least as the hardest problem in the NP class of decision problems) that if solved exactly, by definition, becomes unattractable when the problem's instances increase. We propose two auction-based sub-optimal solutions to an Urban Air Mobility application of the general problem of heterogeneous multi-agent system's task allocation. Auction task allocators' computational complexity is proven to scale as a polynomial function of the number of tasks, agents and rounds, as highlighted by Otte et al. (2020). These task allocators can be implemented in a centralized or decentralized manner; they are adaptable to the available communication infrastructure and can manage dynamic tasks. Auction task allocation works, for centralized implementations, according to a communication protocol between a central allocator (auctioneer) and the system's agents (bidders), repeated every round. The number of tasks advertised and allocated per round depends on the auction strategy and determines the total number of rounds of the algorithm. In sequential single-item auctions, the auctioneer broadcast an unsold task from the task set to each agent, which sends as a response its valuation for that task. The auctioneer awards the task to the agent with the best valuation and the process is repeated until all tasks are sold. In multiple-item auctions, considering the G-prim strategy of Otte et al. (2020), the remaining unsold tasks in the current round are broadcasted, agents evaluate every task, send to the auctioneer their best valuation and the agent with the best valuation is allocated to the corresponding task.

The proposed hybrid algorithms can manage the allocation of heterogeneous tasks to heterogeneous agents thanks to the auction-inspired strategy combined with deterministic scalar optimization: the bid of each UAV for a task is the result of an optimization problem whose cost function and constraints change depending on task type, UAV parameters and minimum risk path length. Both the sequential single-item and the multiple-item auction strategies implement the proposed solutions.

The auction-based task allocation solutions as well as the different energy and flight time optimizers are presented in sub-section 3.1, while an overview of the adopted risk-aware path planner is presented in sub-section 3.2.

3.1. Task Allocation

The first greedy solution we propose consists of *Algorithm 1*. The minimum energy required by each UAV in order to reach a charge station in the worst-case scenario, *i.e.,* the UAV and the station are located at the most distant extremities of the operational area, is computed by *Optimizer*$_1$ which is defined by cost function of Eq. (1) to be minimized subject to constraints of Eq.s (2) with BL^i=1 and E^i_{MIN}=0, (3), (4). $J_1(v^i_j)$ is the energy required by UAV i to perform task j with velocity v^i_j. Such an energy consumption model is taken from the work of Aiello et al. (2021), where an energy estimation method for UAS-based urban logistics is proposed, starting from the Newton's equilibrium in steady state flight conditions. It is worth noticing that this model does not consider cross section variations during the flight, energy for take-off and landing, changes in the airflow directions, different UAV speeds during task execution, etc., yet it provides a satisfactory estimation considering our assumptions. When charge tasks are considered, $L_2{}^i_j$ is set to zero as no payload is carried and $L_1{}^i_j$ denotes the distance between UAV i location and charge station j. Eq. (2) expresses a minimum remaining energy constraint after task completion, while Eq.s (3) and (4) are constraints on the upper and lower bounds of v^i_j.

$$J_1(v_j^i) = \frac{1}{\eta}\left(c_d^i \rho A_d^i \left({L_1}_j^i + {L_2}_j^i \right) {v_j^i}^2 + \frac{{L_2}_j^i \sqrt{\left[\left(m^i + {m_p}_j\right) g\right]^3}}{v_j^i F_M^i \sqrt{2\rho A_r^i}} + \frac{{L_1}_j^i \sqrt{(m^i g)^3}}{v_j^i F_M^i \sqrt{2\rho A_r^i}} \right) \tag{1}$$

$$E_{MAX}^i BL^i - J_1(v_j^i) \geq E_{MIN}^i \tag{2}$$

$$v_j^i > 0 \tag{3}$$

$$v_j^i \leq v_{MAX}^i \tag{4}$$

Each delivery task is assigned to the UAV with the best bid, i.e., minimum energy consumption. UAV i can bid for delivery task j if m_P^j is at most equal to m^i and T_i^i is less than task j's due date. Each bid results from *Optimizer*$_2$, which minimizes the cost function of Eq. (1) subject to Eq.s (2), (3), (4) and (5). Eq. (5) represents the task's due date constraint. ${L_1}^i_j$ and ${L_2}^i_j$ are computed by *RiskAwarePlanner* and given to *Optimizer*$_2$ as constant parameters of cost function $J_1(v^i_j)$. Prior to the start of a new auction round, if the bids list is empty, charge tasks are assigned to UAVs with BL lower than BL_T (set to 30%) in case of multipe-item auction implementation or to UAVs that were able bid in the current auction round for the single-item variant. For each UAV to be charged in the current round, *ChargeTaskAllocator*$_1$ algorithm allocates the station j with shortest minimum risk path to the ith UAV to be charged in the current round and minimizes the flight time to the station by means of *Optimizer*$_c$. This optimizer has cost function of Eq. (6), *i.e.*, the flight time of UAV i to station j, with constraints expressed by Eq.s (2) with $E^i_{MIN}=0$, (3) and (4). With this formulation, each UAV to be charged in the current round is sent to the station with shortest safe path from the location of the UAV itself, which can consume all its remaining energy to reach the assigned station in the shortest feasible amount of time.

$$T_i^i + \frac{{L_1}_j^i + {L_2}_j^i}{v_j^i} \leq T_{DD\,j} \tag{5}$$

$$J_2(v_j^i) = \frac{d_j^i}{v_j^i} \tag{6}$$

Algorithm 1 (Multiple-item auction)

```
for i=1 to M do
    compute E_MIN^i by means of Optimizer_1
r=0
E_TOTAL=0
multiple=1
flag=1
while r≠N do
    if flag==1 do r=r+1
    update unsold tasks from task list
    delete best_bids list
    for i=1 to M do
        for p=1 to N_UNSOLD do
            select unsold task^p
            if m_P^p≤m^i && T_i^i≤T_DD^p do
                compute L_1 and L_2 for UAV^i and task^p by means of RiskAwarePlanner
                compute J_1(v^i_p) by means of Optimizer_2
                if Optimizer_2 finds a solution && J_1(v^i_p)< best_bids^i(1) do
                    best_bids^i= [J_1(v^i_p), p]
    if best_bids^j(1) is the minimum of best_bids (1) list && best_bids list is not empty do
        assign task best_bids^j(2) to UAV^j
        flag=1
        next location of UAV^j = delivery point location of best_bids^j (2)
        update BL^j, T_i^j and set E_TOTAL= E_TOTAL+best_bids^j (1)
    if best_bids list is empty do
        flag=0
        assign charge tasks by means of ChargeTaskAllocator_1
```

Algorithm 1 (Single-item auction)

```
for i=1 to M do
    compute E_MIN^i by means of Optimizer_1
r=0
flag=1
multiple=0
E_TOTAL=0
while r≠N do
    if flag==1 do r=r+1
    select task^r from task list
    delete bids list
    for i=1 to M do
        if m_P^r≤m^i && T_i^i≤T_DD^p do
            set UAV^i as able to perform task^r
            compute L_1 and L_2 for UAV^i and task^r by means of RiskAwarePlanner
            compute J_1(v^i_r) by means of Optimizer_2
            if Optimizer_2 finds a solution do
                put J_1(v^i_r) in bids list of task^r
    if J_1(v^j_r) is the minimum bid && bids list is not empty do
        assign task^r to UAV^j
        next location of UAV^j = delivery point location of task^r
        update BL^j, T_i^j and set E_TOTAL= E_TOTAL+J_1(v^j_r)
        flag=1
    if bids list is empty do
        assign charge tasks by means of ChargeTaskAllocator_1
        flag=0
```

ChargeTaskAllocator₁

```
for i=1 to M do
    if (UAV^i is able to perform task^r && multiple==0) || (BL^i≤BL_T && multiple==1) do
        initialize nearest_station^i
        for k=1 to O do
            compute d for UAV^i and task^k by means of RiskAwarePlanner
            if d<nearest_station^i do
                nearest_station^i=d
                assign task^k to UAV^i
                next location of UAV^i = station location of task^k
                update BL^i
                compute J_2(v^i_k) by means of Optimizer_C
                update T_f^i
```

The second greedy solution we propose consists of *Algorithm 2*, where each delivery task is assigned to the UAV that requires the minimum energy consumption for that task, without imposing a minimum energy constraint after task completion. The bid of UAV i for task j results from *Optimizer*$_3$, which minimizes cost function of Eq. (1) with constraints of Eq.s (2) with BL^i=1 and E^i_{MIN}=0, (3), (4) and (5). Charge tasks are allocated after delivery tasks according to *ChargeTaskAllocator*$_2$ algorithm: if the energy of UAV i after the completion of its assigned task j is less than E_{MIN}^i, given by *Optimizer*$_1$, UAV i is assigned to the charge station with shortest minimum risk path from the previous UAV position, before the execution of task j. *Optimizer*$_c$ minimizes the flight time to the charge station assigned to UAV i, as in *ChargeTaskAllocator*$_1$. The safe path from the updated UAV position to the parcel pick-up position $L_1{}^i{}_j$ is computed again and task j is executed with velocity $v^i{}_j$, previously computed by *Optimizer*$_3$, to limit the increase of the total number of optimization-related iterations of the solution.

Algorithm 2 (Multiple-item auction)

```
r=0
E_TOTAL=0
while r≠N do
    r=r+1
    update unsold tasks from task list
    initialize best_bids list
    for i=1 to M do
        for p=1 to N_UNSOLD do
            select task^p from unsold tasks list
            if m_P^p≤m^i && T_i^i≤T_DD^p do
                compute L_1 and L_2 for UAV^i and task^p by means of RiskAwarePlanner
                compute J_1(v^i_p) by means of Optimizer_3
                if Optimizer_3 finds a solution && J_1(v^i_p)< best_bids^i(1) do
                    best_bids^i= [J_1(v^i_p), p]
    if best_bids^j (1) is the minimum of best_bids (1) list do
        assign task best_bids^j (2) to UAV^j
        next location of UAV^j = delivery point location of task best_bids^j (2)
        update BL^j, T_f^j
assign charge tasks by means of ChargeTaskAllocator_2
```

Algorithm 2 (Single-item auction)

```
r=0
E_TOTAL=0
while r≠N do
    r=r+1
    select task^r from task list
    delete bids list
    for i=1 to M do
        if m_P≤m^i && T_i^i≤T_DD^r do
            compute L_1 and L_2 for UAV^i and task^r by means of RiskAwarePlanner
            compute J_1(v^i_r) by means of Optimizer_3
            if Optimizer_3 finds a solution do
                put J_1(v^i_r) in bids list of task^r
    if J_1(v^j_r) is the minimum bid do
        assign task^r to UAV^j
        next location of UAV^j = delivery point location of task^r
        update BL^j, T_f^j
assign charge tasks by means of ChargeTaskAllocator_2
```

ChargeTaskAllocator₂

```
for j=1 to M do
    compute E_MIN^j by means of Optimizer_1
for i=1 to N do
    if task i is assigned to UAV^j && E_MAX^j BL^j≤E_MIN^j do
        initialize nearest_station^j
        for k=1 to O do
            compute d for UAV^j and task^k by means of RiskAwarePlanner
            if d<nearest_station^j do
                nearest_station^j=d
                assign task^k to UAV^j
                location of UAV^j = station location of task^k
                update BL^j
                compute J_2(v^j_k) by means of Optimizer_C
                update T_f^j of task^i
                compute L_1 for UAV^j and task^i by means of RiskAwarePlanner
                E_TOTAL= E_TOTAL+J_1(v^j_i)
```

3.2. Risk-aware Path Planning

The auction-based task allocation presented above requires the computation of several paths connecting the UAV position to the task positions. To do this, we adopt the use of the risk-aware path planning proposed in our previous work in Primatesta et al. (2018), in which a safe path for UAVs is computed with a two-step procedure: first, a risk map is generated, thus, a path planning algorithm searches for the minimum risk path minimizing the overall risk and the flight time.

As defined in Primatesta et al. (2020a) the risk map is a two-dimensional location-based map in which each element of the map represents a specific location and is associated with a risk value. The risk value is computed with a probabilistic ground risk assessment approach that estimates the expected frequency of fatalities after a ground impact accident expressed in fatalities per flight hour (h^{-1}). The risk assessment considers several parameters such as the population density, the sheltering factor and estimates the impact area and the kinetic energy at impact. For this reason, the risk map depends on the aircraft type and characteristics, *e.g.,* mass, dimensions and maximum flight speed. Hence, a risk map must be computed per each UAV type considered, as well as considering the mass of the payload delivered. For more details about the generation of the ground risk map refer to Primatesta et al. (2020a).

After the generation of the risk-map, a risk-aware path planning strategy is used to compute the minimum risk path in the map. Specifically, we adopt the RRT*, a sampling-based algorithm introduced by Karaman and Frazzoli (2010). RRT* explores the search space, *i.e.,* the map, constructing an asymptotically optimal tree. The near-optimal solution is the branch of the tree connecting the start and goal. In this paper, RRT* is used to minimize the overall risk with respect to the flight time. In fact, the risk, expressed in flight hour (h^{-1}), is proportional to the flight time. For more details about the risk-aware path planner refer to Primatesta et al. (2018).

Before returning the path to the task allocator, we verify that the average risk of the minimum risk path is lower than an Equivalent Level of Safety (ELOS). According to Dalamagkidis et al. (2009), an acceptable ELOS with lightweight UAVs is $10^{-6}\ \mathrm{h}^{-1}$. This last step is essential because the risk-aware path planning returns the minimum risk path in the risk-map, without ensuring that the computed path has an adequate level of safety.

4. Simulation Results

The algorithms are implemented in MATLAB, the communication phases among agents and auctioneer are not implemented and represent a guideline for our solution implementation. For instance, agents' bids are computed and evaluated with for-loops. The path planner is implemented in ROS/C++ and it's called by the algorithms by means of built-in MATLAB functions. The optimizers in the algorithms are solved with the Augmented Lagrange Multiplier method, as formulated in Dong (2006). Unconstrained optimization on the augmented Lagrange function of each constrained optimization problem is performed with the built-in *fminsearch* MATLAB function. A reference scenario with a total number M of 4 UAVs, selected among 4 different types, is considered for the algorithms' evaluation. Details about the fleet's composition and main characteristics are reported in Table 1.

We assume that UAVs' F_M is constant (0.9), as well as c_d (0.3), η (0.8) and ρ (1.23 kg/m^3). The total number N of parcel delivery tasks to be executed within a unique T_{DD} of 3 hours is 15 (case a). The following payloads populate the task set: 5 parcels of 0.5kg, 3 of 1kg, 3 of 1.5kg, 2 of 2kg and 2 of 3kg. The total number O of charge stations is 3. The algorithms are also evaluated considering the same aforementioned scenario, but with each task having a random T_{DD} between 0 and 3 hours (case b). In case b, the task set is ordered according to ascending T_{DD} so that the single-item auction-based solutions can allocate tasks starting from the ones with higher priority.

Table 1. UAVs' fleet characteristics.

UAV type	UAVs' number	m [kg]	A_r [m^2]	A_d [m^2]	v_{MAX} [m/s]	E_{MAX} [MJ]
A	1	1	0.2	0.4	16	0.68
B	1	2	0.28	0.6	19	0.90
C	1	3	0.36	0.8	20	1.17
D	1	4	0.44	1	22	1.43

Before introducing the results of the proposed strategies, we focus on the risk-aware path planning adopted in this work. Fig. 1 shows an example of the risk map computed in a portion of the city of Turin (Italy) considering a UAV type D. On the risk map is also reported a minimum risk path (black line) compared with a line-of-sight (LOS) path (blue line) and a minimum risk path computed considering a UAV type A. In order to highlight the effect of risk-aware path planning, the plot of Fig. 2 reports the evolution of the risk on the map. As expected, the minimum risk path of the UAV type D involves lower risk than the LOS path. Instead, the UAV type A involves lower risk than UAV type D because of the lower mass, dimensions, and maximum speed. This aspect causes a variation of the minimum risk in the map. We want to clarify that the minimum risk path of the UAV type A is computed by evaluating its own risk map.

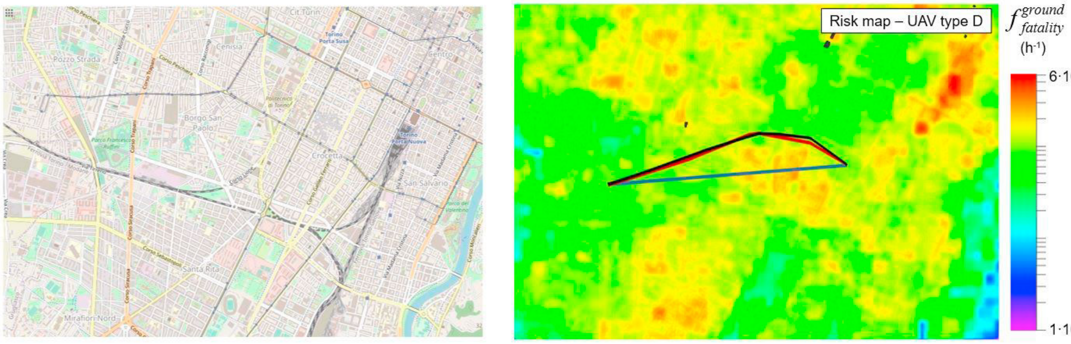

Fig. 1. On the left, the considered portion of the city of Turin (operational area). On the right, the risk map computed with a UAV type D. On the risk-map is reported the minimum risk path (black), the line-of-sight path (blue) and the minimum risk path of a UAV type A (red).

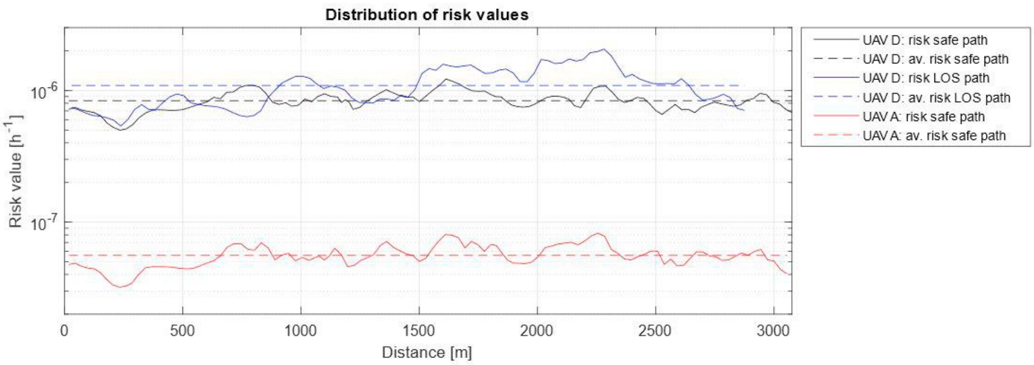

Fig. 2. the distribution of risk values of the paths of Fig. 1.

Simulation results are reported in Table 2. The Monte Carlo simulations are repeated 10 times for both cases a and b. The medium value μ and the standard deviation σ are reported for the following parameters: total energy required by the fleet to execute all assigned tasks E_{TOT}, the number of delivery tasks not assigned NT_{NA}, the number of charge stations visited NT_{CHAR} and the total number of iterations of the optimizers in each algorithm N_{OPT}. At each simulation, the location of UAVs, charge stations and tasks' pick-up and delivery points are initialized randomly within the operational area defined in the portion of the city of Turin, Italy shown in Fig. 1.

The results show that both *Algorithm 1* and *Algorithm 2* represent a valuable solution to the problem. Also, they perform similarly from a computational standpoint. *Algorithm 2*, which allocates all the tasks first and considers the battery discharge afterward, is more promising than *Algorithm 1* as it leads to greater efficiency in terms of minimization of total energy consumption. In case b, when each task has a random due date, NT_{NA} is smaller for *Algorithm 2* because a lower energy consumption implies fewer charge stations to be visited, less time dedicated to charge tasks and more time for executing delivery tasks. Also, *Algorithm 2* ensures a smaller number of unassigned tasks.

Table 2. Simulation results.

Algorithm	E_{TOT} [MJ]		NT_{NA}		NT_{CHAR}		N_{OPT}		T_{DD}
	μ	σ	μ	σ	μ	σ	μ	σ	
1 (single-item)	4.08	0.34	0	0	5	0	153	1	a
1 (multiple-item)	3.51	0.50	0	0	4.5	2.2	346	23	a
2 (single-item)	3.45	0.33	0	0	3	1.4	187	9	a
2 (multiple-item)	3.44	0.16	0	0	4	0	401	21	a
1 (single-item)	3.67	0.53	0.33	0.39	4	1.3	154	16	b
1 (multiple-item)	3.16	0.68	1	0.77	5	1.4	372	95	b
2 (single-item)	3.21	0.73	0.08	0.21	4	1.3	190	34	b
2 (multiple-item)	2.96	0.64	0.25	0.35	3	1.3	466	202	b

The multiple-item implementation of both solutions leads to minor total energy consumption with respect to the single-item variant, as all UAVs can bid for all unsold tasks at each round, but it requires a higher yet still polynomial computational effort. The number of optimization-related iterations is also higher, as the optimizers are called several times at each auction round. On the other hand, the single-item implementations are faster and perform better when considering tasks with priorities since tasks are advertised and allocated in cascade, starting from the one with lower T_{DD}.

5. Conclusions

In this paper, two greedy algorithms for solving a heterogeneous task allocation problem for a fleet of different UAVs are proposed and evaluated with Monte Carlo simulations. The proposed solutions allocate delivery tasks with due date constraints to the fleet members that require less energy consumption and charge tasks in order to address the battery discharge issues of a UAS parcel transportation service. Both the algorithms are auction-based and are implemented by means of a single-item and a multiple-item strategy. Scalar constrained optimization problems are solved to determine the UAV's bid for each task, with variable cost functions and constraints depending on the task considered. The cost function to be minimized is the energy consumption for delivery tasks and the flight time for charge tasks.

We also address the problem of generating safe paths for each task, as the fleet of UAVs is meant to fly over a populated area in an urban environment. The path planner is always able to generate a minimum risk path for each task. Then, the computed path length is given to the optimizers as a parameter.

Simulation results show that both the proposed solutions are able to effectively handle the complexity and heterogeneity of the problem. The multiple-item auction strategy allows to save more energy, but it is less suitable for handling tasks with different due dates. On the contrary, the single-item allocation performs better when tasks have priorities and it's less computationally expensive.

Future works may include the implementation of the algorithms in a distributed software environment, from which the management of dynamic tasks and critical situations such as communication delays can be addressed. A comparison with an exact solution may also be made. Furthermore, the energy consumption model can be improved in order to take into account, apart from the steady state flight phase, other phases of a task completion cycle such as take-off, landing and hovering in place in case of inflight idle time.

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