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An Analysis on Tradable Permit Models for Last-Mile Delivery Drones

FILIPE ALVES NETO VERRI, CESAR A. C. MARCONDES, DENIS S. LOUBACH, (Member, IEEE), ELTON F. SBRUZZI, JOHNNY CARDOSO MARQUES, (Member, IEEE), LOURENÇO ALVES PEREIRA JÚNIOR, MARCOS RICARDO OMENA DE ALBUQUERQUE MAXIMO, (Member, IEEE), AND VITOR VENCESLAU CURTIS

Computer Science Division, Aeronautics Institute of Technology (ITA), São José dos Campos 12228-900, Brazil

Corresponding author: Johnny Cardoso Marques (johnny@ita.br)

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ABSTRACT Drones can play a game-changing role in reducing both cost and time in the context of last-mile deliveries. This paper addresses the last-mile delivery problem from a complex system viewpoint, where the collective performance of the drones is investigated. We consider a last-mile delivery system with a tradable permit model (TPM) for airspace use. Typically, in other research works regarding last-mile delivery drones, a fully cooperative centralized scenario is contemplated. In our approach, due to the TPM, the agents (*i.e.* drones) need to compete for airspace permits in a distributed manner. We simulate the system and evaluate how different parameters, such as the arrival rate and airspace dimensions, impact the system behavior in terms of the cost and time needed by the drones to acquire flight permits, and the airspace utilization. We use a simplified simulation model, where the agents' strategies are naïve, and the drones' flight dynamics are not accounted for. Nevertheless, the simulation's level of detail is adequate for capturing interesting properties from the agents' collective behavior, as our results support. The obtained results show that the system's performance is satisfactory, even with naïve agents and under high traffic conditions. Moreover, a real-world implementation of our competitive decentralized approach would lead to advantages, such as fast permit transactions, simple computational infrastructures, and error resilience.

INDEX TERMS Complex systems, drones, simulation, last-mile delivery (LMD), tradable permit model (TPM), UAV air traffic management (ATM), unmanned aerial vehicles (UAV).

I. INTRODUCTION

Unmanned aerial vehicles (UAV) can play a game-changing part in terms of cost and delivery time reduction to address the *last-mile delivery* (LMD) problem, and also to attend emergencies [1].

The importance of LMD services is increasing, especially considering times where social distance is a must [2]. Many recent studies appoint last-mile as one of the most expensive, inefficient, and polluting parts of the supply chain, reaching about 13-75% of the total supply chain cost [3]. Besides, this is also a concern for major retailers, such as Amazon, Walmart, and Alibaba. Given such scenario, UAVs, also known as *drones*, are of special interest [4].

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Using drones for delivery purposes can have at least four main advantages: autonomy, avoidance of traditional road network, cost, and speed [5]. Drones can be either remote controlled or fully autonomous depending on local regulations. Despite the advantages, there are lots of open problems, such as airspace utilization, payload capacity planning, autopilot and navigation on difficult shadow areas.

Generally, drones are categorized into high altitude platforms (HAP), *e.g.* 17+ km, or low altitude platforms (LAP), *e.g.* tens of meters to few kilometers. HAPs are mostly considered quasi-stationary and have more endurance to face a few days to months campaign. On the other hand, LAPs are agile, cost-effective, and can be faster recharged. Drones are also classified as fixed- or rotary-wings. The former, such as small planes, have higher speeds and can carry more load, however they need to keep moving forward with moderate speeds to stay in the air, making them harder to maneuver. The latter can be represented by quadrotor drones that can hover at low speeds or in place, but their flight autonomy is limited to less than one hour [6] given nowadays battery technology. A hybrid drone is also possible, *i.e.* having fixed- and rotary-wings on the same platform.

According to Alwateer and Loke [7], drones are on the edge of the delivery service. Initiatives in the air traffic management (ATM) system, including SESAR and NextGen, indicate ongoing development along with future communication infrastructure preparations.

Aerial delivery may impact merchandise, courier, food delivery, humanitarian aid, and passenger transport [8]. The last is considered very ambitious but is already being planned. These applications require the agents to plan and execute delivery routes taking into account cost and time minimization, while avoiding collisions with other agents and the environment.

The amount of urban UAV's is expected to grow even more in the next years. One of the foreseen challenges of this growth is how to manage this traffic over people's heads. In this matter, adaptations of different schemes available in the literature on urban motorways traffic (UMT) to urban UAV traffic (UAT) can take place. Such schemes may provide some useful insight for our purpose.

Even though such literature and schemes have been proposed and employed for UMT [9], its application to UAT is not trivial, and should be adapted for the following reasons. Firstly, there is more room for urban airways than motorways. While motorways are limited by the land availability, such constraint is less restrictive on airways. Hence, the chance of congestion on airways is smaller than motorways. Secondly, although the air space congestion is less likely than motorways congestion, the consequences are more complex and serious. We highlight that wide availability does not mean limitlessness: congestions on airways cannot be totally undermined, since they may represent critical situations in terms of safety. Finally, UMT congestions are more likely to occur on bottlenecks [10]. Traditional airspace traffic management schemes avoid congestions, and collisions altogether, by requiring that each aircraft follows a strict path previously planned by a central unit. However, such schemes might not be appropriate to deal with the traffic and the responsiveness requirements of LMD drones.

In this paper, we consider *tradable permit models* (TPM) proposed by Akanatsu and Wada [11], in connection with *drones route planning*. TPM is an innovative approach to deal with capacity allocation that uses a market mechanism to assign rights to users of a particular resource [9]. Permit schemes has received growing attention in nowadays academic studies. Permit's decentralized nature brings advantages over centralized approaches [12]. In the context of LMD, we consider the airspace as the resource of interest.

We simulate LMD drones (*i.e.* agents) route planning, in a tradable permit model, under different *arrival* rates by focusing on two main perspectives:

1) the *investigation on the collective agent performance*: we assess how long the agents take to complete their mission in different cases, and measure the costs of acquiring all the needed permits; and
2) the *investigation on the four-dimension airspace utilization*: under different arrival rates, we estimate the effective airspace utilization taking into account 3D waypoints (*i.e.* latitude, longitude, altitude) along with time.

Therefore, the contributions of this paper are two-fold:

1) we introduce the concept of *tradable permit models in the context of last-mile delivery (LMD) drones*. To the best of our knowledge, the previous related works in this area have been considering a *fully* cooperative scenario [13]–[16]. However, full cooperation does not capture the competition for airspace utilization between different players; and
2) we analyze how different parameters, such as airspace dimensions and drones' arrival rate, impact the *collective agent performance* and the *airspace utilization* in this scenario. Even with a simplified simulation model, we show that interesting properties emerge from the agents' collective behavior. From a practical perspective, the conclusions drawn from our results could drive how airspace policies are defined.

We point out that the analyses shown herein consider a *simplified simulation model*, where the drones' flight dynamics are not taken into account and the agents execute the planned routes perfectly. Nevertheless, the simulation's level of detail was adequate for capturing interesting properties from the agents' collective behavior, as the simulation results show.

The remainder of this paper is organized as follows. Section II reviews related literature. Section III describes the computational experiments, while Section IV presents the results of these experiments along with a discussion. Finally, Section V brings the outcomes, and indicates possible future works.

II. RELATED WORKS

Command and control for air traffic is an established research field mainly for safety and regulation purposes. In recent years, many articles have explored the control of small UAVs (*e.g.* drones) for economic opportunities, especially for delivery applications. Many of these applications are enabled by cooperative and collaborative autonomous control, as discussed in [17]–[20].

Besides, autonomous route control is a robust approach with reactive responses to unexpected events. It may decrease chances of collisions in a real environment where each company is free to perform its particular route control. It may also result in inefficiency and congestions in areas with a high density of UAVs, thus increasing the complexity of collision avoidance systems and the network traffic among UAVs.

To overcome those issues, other researches [13]–[16] propose some level of centralized control optimize costs and improve collision avoidance. In that architecture, UAVs are more passive than the previous ones. Collision avoidance is achieved during path planning, computing occurs in a central unit where more processing capacity is available, and the holistic view of the fleet enables optimal solutions.

Furthermore, it is reasonable to expect that when using a collision avoidance scheme during the path planning, collision avoidance maneuvers will occur only in unexpected and rare events, offering greater security. However, optimal solutions can be unfeasible to compute since routing and scheduling are well-known NP-hard problems. Specifically, collision avoidance and trajectory optimization of UAVs can be studied as the traditional vehicle routing problem (VRP) in operational research and combinatorial optimization [16].

To the best of our knowledge, there is a lack of researches considering efficient route control for UAVs in areas with a high density of vehicles and free choice of routes for companies in practical time.

Our proposal is based on the concept of a tradable permit scheme, introduced in the 1960s by Crocker [21] and Dales [22], for externality regulation in atmospheric and water pollution applications, respectively. In his original article [22], Dales compares empirically the benefits of rent theory for water use and rising land over 350 years. He states a direct relationship between the level of rent and the development of technologies. While water use was renting-free, there was over-use and virtually zero improvements. On the other hand, the land rent system forced a rational use, leading to important improvements in land-use technology.

Since that time, many tradable permit schemes have been developed and applied in a variety of fields: environmental regulations [23], [24], fishing [25], agriculture [26], and others. Early implementations of tradable permits in the field of transport capacity allocation were proposed for airport slot allocation to improve the efficiency of runway usage [27], [28] and for roadway capacity allocation [29], [30].

For roadways, the road pricing alternative was preferred in real implementations especially because of the cost of monitoring and the technological resources at the time. However, tradable permits have been attracting attention in recent years due to the current technology, especially the low cost of transactions over the Internet [11], [31]–[34]. We emphasize that these articles are related to road transportation and, to the best of our knowledge, the literature lacks applications of tradable permit schemes for air traffic control of UAVs.

Besides the first tradable permit studies focused on conceptual developments [29], [30], [35] for managing congestion, recent works started to apply quantitative analysis [9], [10], [31], [36]–[39], and simulations [40] to explore different types of schemes.

Although road tradable permit is a transport application, UAV imposes very different dynamics, *e.g.* safety and security are much more critical, and autonomy and range of work are very compromised, especially for delivering drones.

Since we deal with a competitive scenario, the market simulation of our TPM is a simplification of the model proposed by Iori and Chiarella [41]. They introduce an order-driven market model with heterogeneous agents trading via a central order matching mechanism in a double auction, dispensing the need for a controller. At the moment of ordering, agents face three different parameters in their decision: the price (limited at some value or marketed), the direction (long or short) and the volume or the level of leverage. Moreover, the agents have intelligence in order to decide the price and the direction (buy or sell) and are allowed to trade even though they have no goods.

They propose a model with three different components. The first component, called fundamental, gives the intrinsic value of the good. For example, in the case of stocks, the intrinsic value of the company is calculated using the information in its balance sheet. The fundamental component indicates to sell (buy) when the price is higher (lower) than the stock intrinsic value or fundamental price.

The second component is the chart. It uses historical data instead of the intrinsic value. The chartist component can be divided into contrarians and trend followers. Contrarians are based on the existence of overreaction in prices [42]. This indicates to buy (sell) past losers (winners). Unlike the contrarians, trend-followers are based on the existence of trends on prices [43]. This indicates to buy (sell) past winners (losers).

The third component is called noise. This component does not follow any standard or pre-defined behavior. This indicates decisions using no strategy and zero-intelligence.

In comparison to these related state-of-the-art researches, our main contributions are: a) adaptation of a TPM to consider airspace as the resource of interest; and b)introduction of a scheme of UAV route control in a decentralized competitive manner using such a TPM.

III. EXPERIMENTS DESCRIPTION

This section details how we simulate the collective dynamics of interacting agents bidding for flight permits considering a TPM context.

A. OVERVIEW

First, we discretize time and space in arbitrary units. As a consequence, each permit is uniquely identified by a tuple (x, y, z, t), such that x, y, z, and $t \in \mathbb{Z}^{0+}$ (*i.e.* positive integers including zero) represents latitude, longitude, altitude, and time, respectively. The size and the timespan of each permit depend on the discretization. The airspace is limited in each simulation by the dimension limits X, Y, and Z, such that $0 \leq x < X, 0 \leq y < Y, 0 \leq z < Z$. Simulations start at $t = 0$.

To simplify, we assume the agents only move in directions parallel to the Cartesian axes, *i.e.* we forbid diagonal moves. Moreover, each agent moves exactly one unit of space in one unit of time. Therefore, formally, in terms of both space and time, we define that permits (x_a, y_a, z_a, t_a) and (x_b, y_b, z_b, t_b) are adjacent if, and only if, $|x_a - x_b| + |y_a - y_b| + |z_a - z_b| = 1$ and $|t_a - t_b| = 1$.

Algorithm 1 gives an overview of the simulation.

At each time step t, up to λ new agents arrive at the system. The parameter λ is called *arrival rate* and is fixed during the simulation. For each simulation, exactly N agents are generated. Thus, at time $t \geq \lceil N/\lambda \rceil$, no new agent arrives at the system (See lines 1–3,17–19 in Algorithm 1).

After new agents arrive, each one of them bids for permits given a random mission. A mission consists of a starting point (x_s, y_s), and an ending point (x_e, y_e). Given a mission, each agent a tries to achieve a sequence of adjacent permits $\pi = \langle p_1, p_2, \ldots, p_l \rangle$ such that $p_1 = (x_s, y_s, 0, t)$ and $p_l = (x_e, y_e, 0, t+l)$ for some $t > t_a$ and $l \geq 2$, where t_a is the time agent a arrived (See lines 8-9 in Algorithm 1).

Notice that agents enter the simulation without owning permits. However, they may eventually own unused permits due to an unsuccessful attempt in acquiring a sequence completely in a given iteration. Since each permit is negotiated individually, an agent may lose the auctions for some permits. Then, in the next iteration, a newly computed shortest sequence may not contain all the owned permits by this agent.

The agent's strategy is naïve. An agent a tries to find the shortest sequence of available[1] permits to accomplish the mission, preferring sequences that contains more owned permits, and it offers (*i.e.* bids) a random value with the probability distribution in Eq. (1) for each permit it currently does not own. Then, all agents put the permits they own but do not belong to the shortest sequence for sale in the next iteration (See line 10 in Algorithm 1).

After each agent acts in an iteration, the bids are computed and the trades are realized. Each permit for sale, including the ones owned by no agent, that received a bid is transferred to the agent that offered the greatest value (See line 13 in Algorithm 1).

All agents that successfully bought the whole sequence stop bidding for new permits (See line 6 in Algorithm 1).

B. ASSUMPTIONS

For the sake of simplicity, we consider the following assumptions about the simulation:

- we assume all players will use drones with the same speed;
- we do not simulate the flighting phase, only the route planning and the permit acquisition within a TPM context;
- we do not take into account possible collisions of drones coming from opposite directions (in a real-world scenario players would need to consider such restrictions before flying); and
- we assume all drones start and end its mission on the same fixed altitude, *i.e.* $z = 0$.

[1] A permit p is available to agent a if it satisfies one of the following: a owns the permit p; permit p is owned by an agent other than a but it is also for sale; or the permit p is owned by no agent.

Algorithm 1 Simulation Overview Pseudocode

1: Inactive $\leftarrow$ newAgents(N)
2: Active $\leftarrow$ sample(Inactive, λ)
3: $t \leftarrow 0$
4:
5: **while** Active $\neq \{\}$ **do**
6:     Active $\leftarrow$ Active $\setminus$ {agent $\in$ Active : missionAccomplished(agent)}
7:     **for all** agent $\in$ Active **do**
8:         findSequence(agent)
9:         doBids(agent)
10:         doAsks(agent)
11:     **end for**
12:
13:     tradePermits()
14:
15:     $t \leftarrow t + 1$
16:
17:     Active′ $\leftarrow$ sample(Inactive, λ)
18:     Active $\leftarrow$ Active $\cup$ Active′
19:     Inactive $\leftarrow$ Inactive $\setminus$ Active′
20: **end while**

C. AGENT's ACTIONS

The core behavior of each agent consists of choosing the permits it bids for. Basically, the process is presented in Fig. 1, which contains N simulated agents, each of them trying to buy a sequence of permits that accomplishes a randomly assigned mission. At each time t, λ agents enter the system and become active. The remaining agents wait for the designated time t. An active agent acts until it achieves its goal.

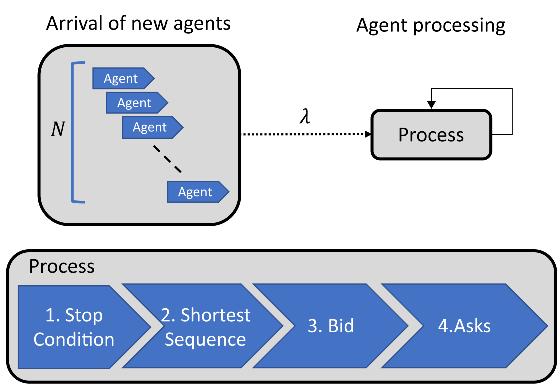

FIGURE 1. Simulation overview and agent actions.

At each time step, as illustrated in Fig. 1, agents:

1) Check for the stop condition;
2) Find the shortest sequence of permits;
3) Bid for missing permits; and
4) Put unused permits for sale (*i.e.* ask).

1) DETAILS ON THE STOP CONDITION

At the beginning of the iteration, each agent knows an updated list of permits it owns. From that list, the agent checks whether a sequence of adjacent permits that fulfills its mission does exist. If it does, the agent places every other permit for sale and stops acting. Otherwise, the agent proceeds to the next step, *i.e.* shortest sequence finding.

2) DETAILS ON THE SHORTEST SEQUENCE FINDING

The next action after verifying the stop condition consists of finding a sequence of permits to bid for. Each agent has a potentially different mission, with starting point (x_s, y_s) and ending point (x_e, y_e), and a maximum waiting time t_0, initialized with $t_0 = 1$. The updates related to the value of t_0 are kept along different iterations. Given a time frame within t, the agents perform the following sub-steps to find the sequence of permits:

- Sub-step I Set the sequence $T = \text{shuffle}(\langle 1, 2, \ldots, t_0 \rangle)$, where T is a random permutation of the input sequence;
- Sub-step II For each $\tau \in T$:
  - a) Use A* search algorithm [44] to find the shortest sequence of available permits π with length $|\pi|$ that connects $(x_s, y_s, 0, t + \tau)$ to $(x_e, y_e, 0, t + \tau + |\pi|)$. Our A* heuristic prefers shorter sequences and, in case of ties, it prefers the ones that contains more owned permits. If ties still occur, we prefer "straighter paths".
  - b) If a sequence does not exist, try the next τ.
  - c) If a sequence exists, go to the next step (as detailed discussed in SectionIII-C3).
- Sub-step III If it cannot find a sequence, update t_0 to 2 t_0 and go to Sub-step I.

In summary, each agent looks for a short sequence π that accomplishes its mission. When a sequence cannot be found, the agent tries a different time τ to start the flight. The more attempts to find a sequence, the longer the waiting time τ tends to be.

Our naïve strategy to avoid permits that receive too many bids is roughly based on the exponential backoff algorithm [45]. Considering we have several agents bidding concurrently, the natural selfish behavior leads to sparse possessing of permits. Random and uncoordinated attempts of acquiring sequences cause collision among the player's path. Thus, too few agents accomplish the sequence to deploy the mission. We can use an approach inspired by the random access scheme for packet networks to tackle this problem. As players compete for permits, our strategy is to adopt a backoff algorithm and postpone t_0 to the near future. Then, we progressively move the sequence T (see Sub-step I) into a time range that increased exponentially. Hence, observe offloading the player's demand settling in subsequent time.

3) DETAILS ON THE MARKET SIMULATION

For the purpose of this experiment, our market simulation is a simplification of the model proposed by Iori and Chiarella [41]. After an agent a finds the sequence π of adjacent permits, it offers (*i.e.* bids) a value $b = B_a(\omega)$ for each permit it currently does not own. Each value b is a realization of the random variable B_a from a sample space Ω given a sampled point $\omega \in \Omega$.

For each agent a, the random variable B_a is given by

$$B_a = \mu_a - |S_a| \,, \tag{1}$$

where the value $\mu_a \in [\mu_{\min}, \mu_{\max}]$ is constant in the simulation. S_a is a random variable such that $S_a \sim \mathcal{N}(0, \sigma_a)$ where $\sigma_a \in [\sigma_{\min}, \sigma_{\max}]$ is also constant and $\mathcal{N}$ is the normal distribution. Before the simulation starts, we choose μ_a and σ_a uniformly for each agent a. The parameters μ_a and σ_a are analogous to the fundamental price and the noise, respectively, proposed by Iori and Chiarella[2] [41].

Finally, agents put the permits they own but do not belong to the sequence π for sale in the next iteration.

The trading mechanism we use in the simulation is rather simple. At each iteration, all bids are computed, and for each permit, the agent that offered the highest amount gets it. Only the permits that were made available for sale or does not belong to any agent are traded. When the permit is traded, the cost of each agent is updated. In other words, if the permit is traded with value b, the cost of the agent that buys the permit receives an increment of b, and the one selling off, a decrement of b. Agents have no budget limit.

D. ILLUSTRATIVE EXAMPLE

To clarify the simulation steps, we provide an example of our experiments as shown in Fig. 2.

For the sake of simplicity, in this example, we consider a 2-dimensional airspace, where altitude is not considered. Then, permits are given by (x, y, t) with x, y, and t representing latitude, longitude, and time, respectively.

In this example, two agents are active at time $t = k$. The agent "blue" (*i.e.* dot in blue color) seeks to find a sequence of permits from (0, 1) to (2, 1), while agent "red" (dot in red color), from (1, 0) to (1, 2).

- Fig. 2 (a), at time $t = k$, agent "blue" already owns the permit $(2, 1, k + 3)$, and the stop condition (*i.e.*, whether the sequence of permits that accomplishes the mission was found) is not met yet. Both agents go to the next step.
- Fig. 2 (b), both agents look for the shortest sequences of available permits that accomplish their respective missions.
- Fig. 2 (c), next, they bid a random value for each permit. Since agent "blue" already owns permit $(2, 1, k + 3)$, it only bids for the two missing permits.
- Fig. 2 (d), since they own no unused permit, they proceed to the next iteration.
- Fig. 2 (e), before the next iteration begins, permits are traded considering the offers. The permit $(1, 1, k + 2)$ received bids from both agents.

[2]The second component (*i.e.* chart) is ignored in our simplified simulation.

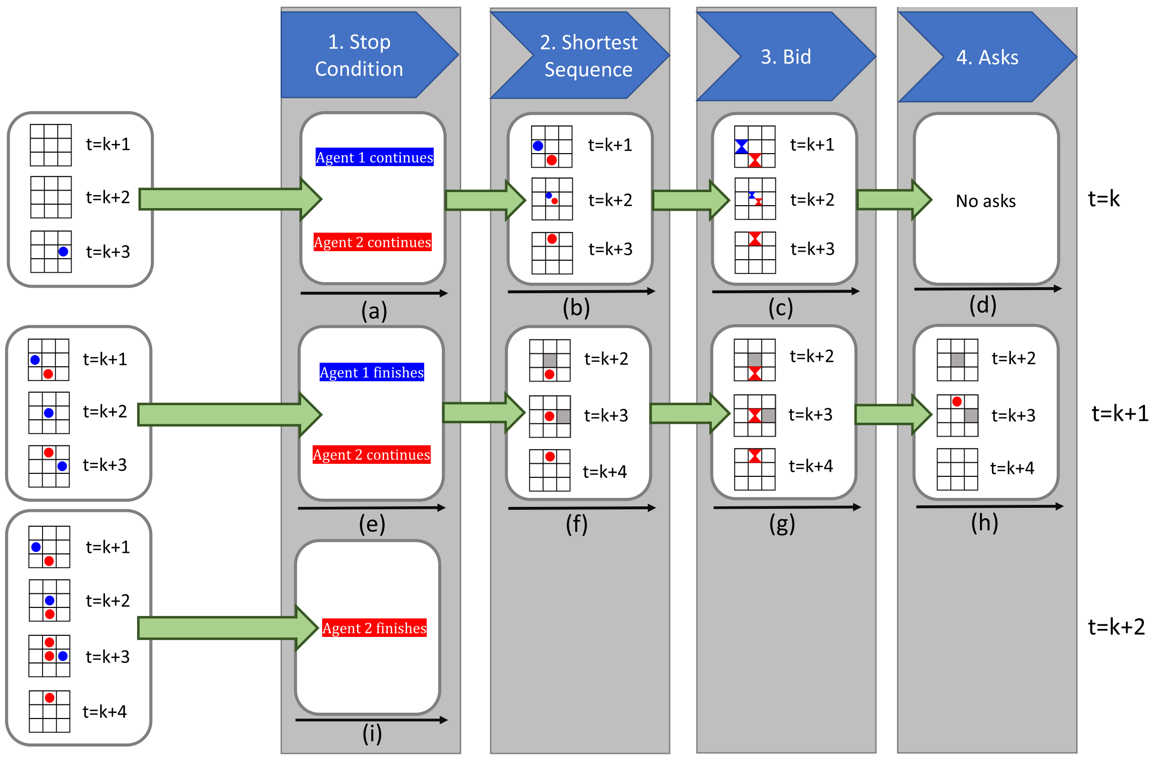

FIGURE 2. **Illustrative example of the simulation.**

In this example, agent "blue" bade the highest value, so it gets the permit. All other permits receive only one offer. At time $t = k + 1$, agent "blue" have got all needed permits and stops acting on the system. Agent "red" continues in the system.

- Fig. 2 (f), agent "red" finds another sequence of available permits starting at time $t = 2$.
- Fig. 2 (g), agent "red" bids a random value for available permits starting at time $t = 2$.
- Fig. 2 (h), the owned permit $(1, 0, k+3)$ is unused and, then, it is placed for sale.
- Fig. 2 (i), after auction results are calculated, agent "red" owns four permits as no other agent bade for the permit that was for sale. Finally, at time $t = 2$, agent "red" has accomplished its mission and stops acting in the system.

Then, simulation stops.

E. PARAMETERS

Table 1 summarizes the simulation parameters and the values we used in this paper. The choice of the airspace dimensions, the arrival rate and the number of agents is arbitrary, as we are interested to study the relationship between them and not absolute values. Also, we choose the interval for the bid fundamental and its deviation (noise) so agent have different fundamental values and their bids have low variation.

TABLE 1. **Simulation parameters.**

Parameter	Symbol	Values
Airspace dimensions	(X, Y, Z)	$(10, 10, 3)$, $(15, 15, 3)$, $(15, 15, 5)$, and $(30, 30, 5)$
Arrival rate	λ	1, 2, 4, 5, 8, 10, 16, 20, 25, 32, 40, 50, 80, 100, 125, 160, 200, 250, 400, 500
Number of agents	N	8000
Bid fundamental	$[\mu_{\min}, \mu_{\max}]$	$[50, 150]$
Bid noise	$[\sigma_{\min}, \sigma_{\max}]$	$(0, 0.2]$

IV. RESULTS AND DISCUSSION

In this section, we present the simulation results. The goal of our investigations is to assess the behavior of the complex system under different *arrival* rates. We focus on two main perspectives:

1) the *investigation on the collective agent performance*: we study how long agents take to complete their mission in different situations, and measure the costs of acquiring all the needed permits; and
2) the *investigation on the airspace utilization*: under different arrival rates, we verify the effective airspace utilization.

A. COLLECTIVE AGENT PERFORMANCE

We simulate the system 20 times for each combination of parameters as shown in Table 1. The results presented in this section are related to those simulations. Notice that we have $N = 8000$ agents per simulation, therefore $20 \times 8000 = 160{,}000$ agents in total. Since our results encompass statistics regarding agent behavior, 20 simulations are enough for obtaining statistically significant results.

An important parameter to assess is the cost each agent incurs in order to accomplish its mission. Since missions differ among agents, we introduce the concept of *relative cost* of an agent. The relative cost of agent a is given by

$$\frac{C_a}{\mu_a L_a}, \tag{2}$$

where C_a is the total cost of agent a during the simulation, *i.e.* expenses to buy permits subtracting the income from selling unused permits, and L_a is the length of the shortest sequence of adjacent permits to accomplish the mission disregarding their availability. By Eq. (1), the value μ_a is an overestimation of the price the agent a pays for a permit.

Fig. 3 shows the relative cost of the agents along with different values of arrival rate. We observe that the cost does not increase linearly with the arrival rate. In fact, we can observe interesting peaks and variance oscillations.

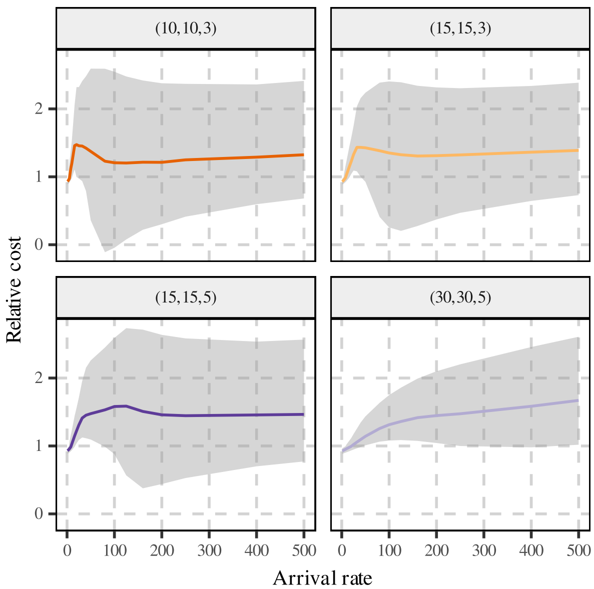

FIGURE 3. Relative cost, Eq. (2), of the agents under different arrival rates λ. Airspace dimensions are indicated on the top of each plot. The solid line is the median relative cost over 20 simulations with $N = 8000$ agents each. Shadows indicate the first and the third quartiles.

Fig. 4 explicits the average and variance of the relative cost for airspaces concerning the dimensions (10, 10, 3) and (15, 15, 3).

We notice four different system's behavior depending on the arrival rate:

1) *Ideal relative cost with almost no variance.* When the arrival rate is sufficiently low (threshold of the transition depends on the airspace size, see Table 2), the average relative cost value remains under 1.0 and the variance approaches 0.0;
2) *Peak relative cost with low variance.* By increasing the arrival rate, the average relative cost reaches the first peak while keeping low variance among agents;
3) *Decreasing relative cost with maximum variance.* Beyond the point of the first peak of the relative cost, the variance still continues to increase. The arrival rate with higher variance coincides with a valley of the average cost; and
4) *Increasing relative cost with decreasing variance.* For higher arrival rates, the average relative cost tends to increase while the variance tends to decrease.

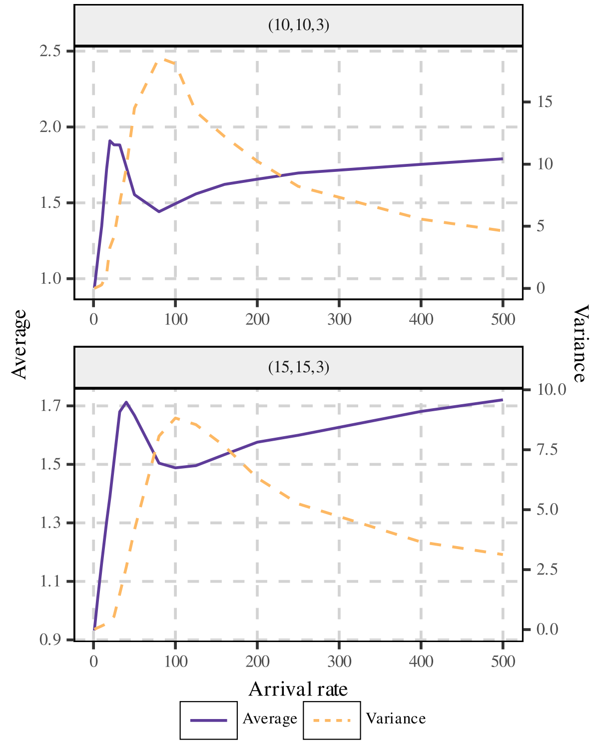

FIGURE 4. Average relative cost (solid dark lines), Eq. (2), and its variance (dashed light lines) under different arrival rates. Airspace dimensions are indicated on top of the plot. The average and variance over 20 simulations with $N = 8000$ agents each.

Similar behavior is also present in larger airspaces, however, peaks and valleys are smoother. One would need greater and finer values of arrival rate as well as more agents in the simulation to better observe the phenomena in larger airspaces. Table 2 shows the values of arrival rate in which the average relative cost and relative cost's variance reaches a peak for different airspace dimensions. In this sense, one can observe that:

- the average first peak and variance peak increase with the airspace size;
- the variance peak is always greater than the average first peak, however, the larger the airspace, the closer the peaks are; and

TABLE 2. Arrival rates in which the average relative cost or the relative cost's variance reaches a peak for different airspace dimensions. The value of the peak is shown between parentheses.

Dimensions	Average First Peak	Variance Peak
$(10, 10, 3)$	$\lambda = 20$ (1.9)	$\lambda = 80$ (18.6)
$(15, 15, 3)$	$\lambda = 40$ (1.7)	$\lambda = 100$ (8.8)
$(15, 15, 5)$	$\lambda = 80$ (2.0)	$\lambda = 160$ (12.8)
$(30, 30, 5)$	$\lambda = 200$ (1.6)	$\lambda = 250$ (2.2)

- the relationship between the arrival rate and the value of the peaks seems to be not trivial.

We are also interested in assessing how long each agent takes to accomplish its mission. Fig. 5 shows the number of iterations the agents participated in the auction before completing their mission. As expected, the number of iterations increases with the arrival rate. Although the curve is steeper in smaller airspaces, beyond a certain arrival rate, the median of the number of iterations shows to be bounded from above by a value close to 7.5. It means that, even with many agents competing to each other, they reach consensus in a reasonable time with the proposed naïve strategy. We expect that more robust bidding strategies would decrease the number of iterations in the auction. We hypothesize that the relatively small number of iterations is due to our strategy to choose t_0 (see Section III-C2).

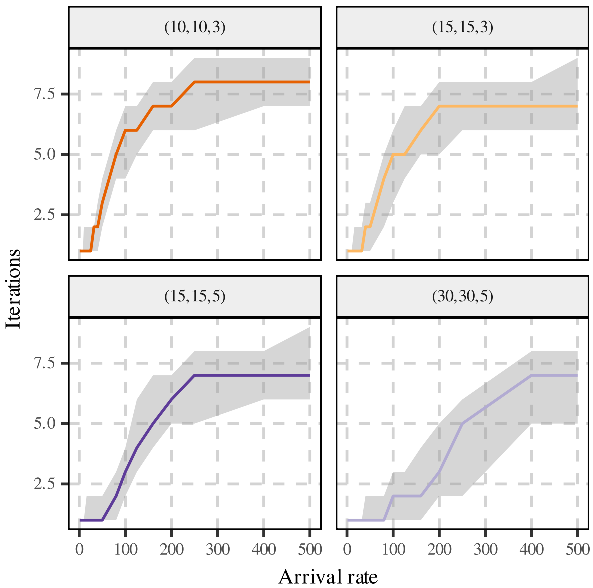

FIGURE 5. Number of iterations in the auction before complete the mission under different arrival rates λ. Airspace dimensions are indicated on the top of each plot. The solid line is the median number of iterations over 20 simulations with $N = 8000$ agents each. Shadows indicate the first and the third quartiles.

Fig. 6 shows the wait time τ value of the sequence that accomplishes the mission under different arrival rates λ. Notice that, for small λ (*i.e.* ≈ 0), the agents find a sequence of permits with starting time close to the current time t. However, after a critical arrival rate, depending on the airspace

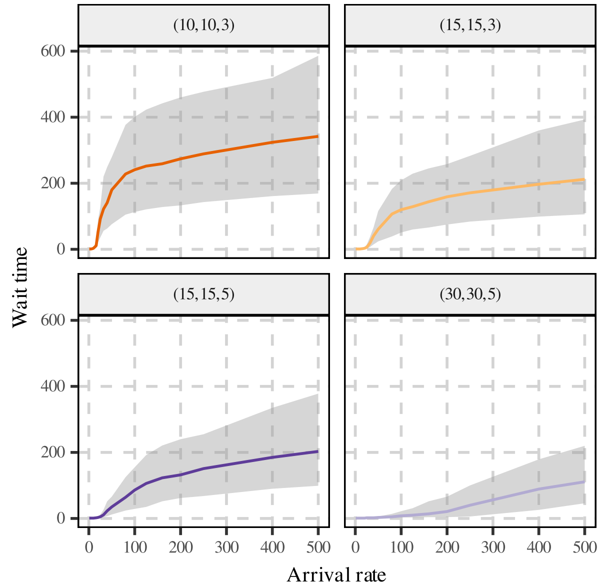

FIGURE 6. Wait time τ of the sequence that accomplishes the mission under different arrival rates λ. Airspace dimensions are indicated on top of the plot. The solid line is the median wait time over 20 simulations with $N = 8000$ agents each. Shadows indicate the first and the third quartiles.

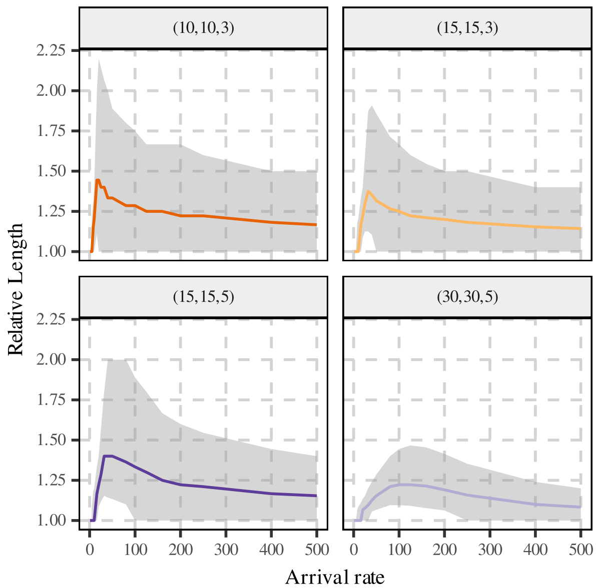

FIGURE 7. Relative length of the final sequence of permits, Eq. (3), under different arrival rates λ. Airspace dimensions are indicated on the top of each plot. The solid line is the median relative length over 20 simulations with $N = 8000$ agents each. Shadows indicate the first and the third quartiles.

size, the value of τ increases rapidly. It means that, under our auction strategy, agents take few iterations to find a sequence, but the starting time of the permits may become high to avoid jamming.

It is also important to assess the size of the sequence each agent finds out. A flight in a path that is too long may be unfeasible in practice.

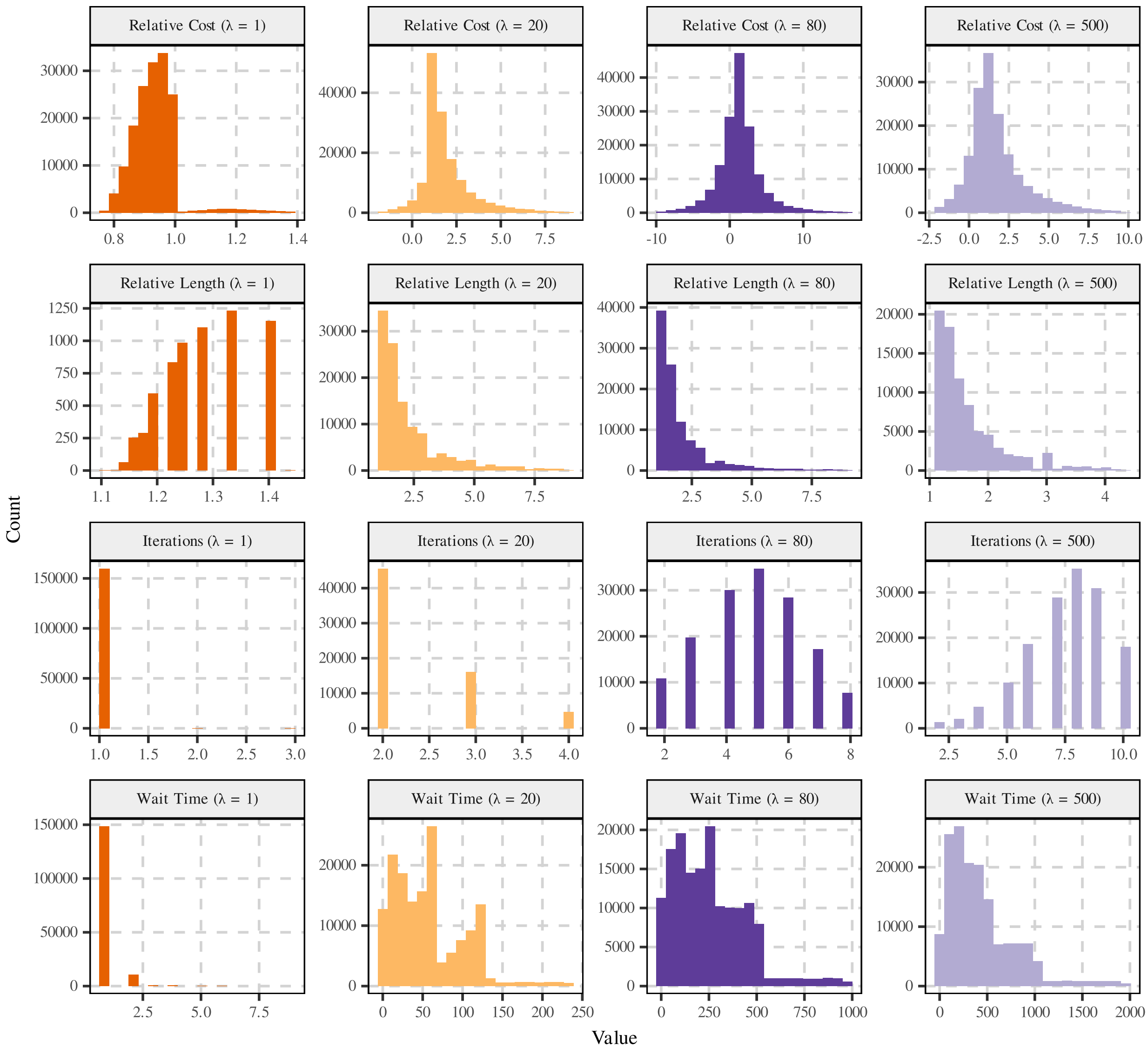

FIGURE 8. **Histogram of metrics of interest (relative cost, relative length, number of iterations, and wait time) under different arrival rates (λ). Airspace dimension is fixed to (10, 10, 3). The metric and the arrival rate are indicated on the top of each plot. In order to improve visualization, limits of the x-axis are the 1st percentile and the 99th percentile of the metric.**

Since missions differ among agents, we introduce the concept of *relative length* of the sequence that accomplishes the mission. The relative length of agent a is given by

$$\frac{L'_a}{L_a}, \tag{3}$$

where L'_a is the length of the sequence agent a uses to accomplish the mission and L_a is the length of the shortest possible sequence of adjacent permits that would accomplish the mission disregarding permit availability.

Fig. 7 shows the relative length of the sequences under different conditions. Notice that the results are similar to the relative cost of each agent. For most values of λ, the agents find out sequences with length under two times the shortest possible length.

By investigating the collective agent performance, we show that, even using a naïve strategy, the problem of route planning and permit acquisition can be solved in a competitive decentralized fashion. Fig. 8 illustrates the histogram of the metrics of interest under different arrival rates and fixed airspace size (10, 10, 3). The majority of the agents:

- spend less than the expected (sometimes even profit[3]); and
- acquire a permit sequence that is short using few auction iterations.

In scenarios with larger arrival rates, such properties are kept at the cost of increasing the wait time.

Fig. 8 also gives a detailed understanding of the four previously identified behaviors depending on the arrival rate λ. We name these states as "no" ($\lambda = 1$), "low", "medium", and "high competition" as a function of the arrival rate.

[3] Agents may profit due to selling unused permits for prices higher than what they paid for.

TABLE 3. Qualitative summary of agent's performance under different arrival rates conditions. The range of the arrival rate (λ) in low, medium, and high competition conditions depends on the airspace dimensions.

Condition	Relative Cost	Relative Length	Iterations	Wait Time
No competition ($\lambda = 1$)	Ideal (with low variance)	Short	Ideal	Low
Low competition	Low (with low variance)	Medium	Few	High
Medium competition	Low (with high variance)	Medium	Few	Very high
High competition	Low (with medium variance)	Short	Medium	Very high

The range of the arrival rate for each state depends on the airspace dimension. Table 3 summarizes the metrics of interest in each one of these states in a qualitative manner.

B. AIRSPACE UTILIZATION

We also investigate how our proposed strategy impacts airspace utilization. Since agents might obtain a partial sequence, due to competition, some permits may be traded but never belong to a sequence that accomplishes the mission. Moreover, other permits may never be traded at all.

In this section, we assess the proportion of permits that are traded and effectively used (*i.e.* belong to a sequence that accomplishes the agent's mission) under different conditions. Fig. 9 shows the airspace usage over different arrival rates at the time-slice that the last agent enters the system ($t = \lceil N/\lambda \rceil - 1$). The proportion of traded permits reaches a peak and then decreases as the arrival rate increases. This is due to agents finding out permit sequences with greater wait time τ. Similar behavior happens for the effectively used permits, although the proportion is lower as expected. For both metrics, the variation over the simulations is negligible.

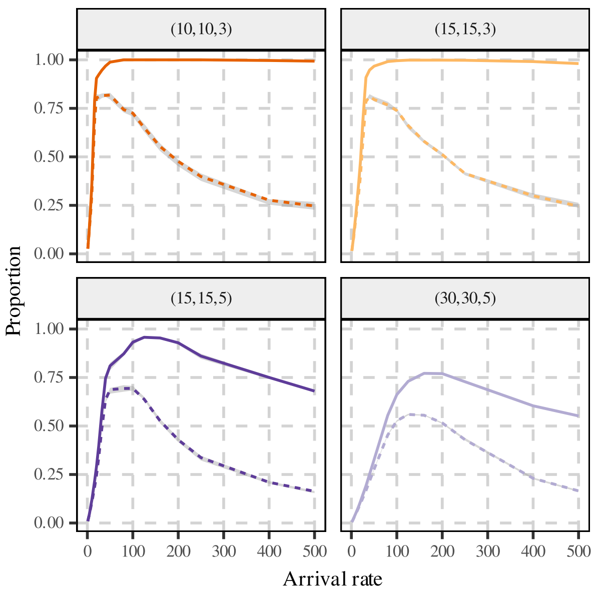

FIGURE 9. Proportion of traded (dashed line) and effectively used (solid line) permits $(x, y, z, \lceil N/\lambda \rceil - 1)$ under different different arrival rates (λ). Airspace dimensions are indicated on top of the plot. Solid lines are the median of 20 simulations. Shadows indicate the first and the third quartiles.

The ratio of effectively used permits over the traded permits also decreases as the arrival rate increases, as seen in Fig. 10. It indicates that in scenarios with high competition, many of the traded permits are never used. As a result, resources are wasted. On the other hand, such a phenomenon does not make the agent's performance prohibited (assessed in Section IV-A) and suggests that there is still room for improvement. For instance, we expect to find out a more robust strategy that keeps the agent's performance while optimizing airspace utilization.

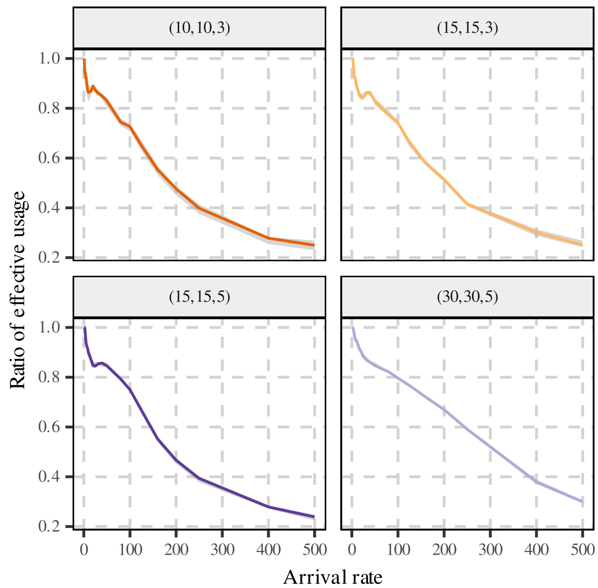

FIGURE 10. Ratio of effectively used and traded permits $(x, y, z, \lceil N/\lambda \rceil - 1)$ under different different arrival rates λ. Airspace dimensions are indicated on top of the plot. Solid lines are the median of 20 simulations. Shadows indicate the first and the third quartiles.

V. CONCLUSION

In this paper, we proposed an alternative solution to the problem of route planning in airspaces. Instead of solving hard centralized cooperative optimization problems, we showed that a naïve decentralized competitive approach yields satisfactory results even under high traffic conditions. As an outcome, our proposal brings the following advantages:

- It avoids a central unit that controls the route planning. We argue that such a decentralized functioning can lead to many advantages in a real-world implementation, such as faster auction results, simpler and cheaper infrastructure, and greater error resilience; and

- It gives freedom to the players to use the airspace in the way that most fits their needs. Players can use smart planning to maximize the usage of the acquired permits. They would still be responsible for collision avoidance and other flight details among their drones, but they would have the guarantee that no other parties would be using their airspace.

Moreover, we showed that not only the naïve agent's performance is satisfactory, but also there is evidence that smarter agents can behave even better.

Since we addressed the permit acquisition model, further studies are required to assess issues concerning also infrastructure, flight, and realistic parametrization. Limitations of our simulation include: a) the distance and time units in our simulations are arbitrary; b) possible errors and failures in the flight phase are not taken into account; and c) we assume all drones fly at the same speed.

In future works, we plan to study agents that use smart strategies, including the use of reinforcement learning [46]. Analytical studies are also planned to be conducted to explain the phenomena under different arrival rates. Such studies can provide tools to control the system in practical applications to make it feasible. Finally, a cyber-physical system can use our tradable permit model to obtain a global consensus for smart cities' missions.

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REFERENCES

[1] K. Dorling, J. Heinrichs, G. G. Messier, and S. Magierowski, "Vehicle routing problems for drone delivery," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 47, no. 1, pp. 70–85, Jan. 2017.

[2] V. Chamola, V. Hassija, V. Gupta, and M. Guizani, "A comprehensive review of the COVID-19 pandemic and the role of IoT, drones, AI, blockchain, and 5G in managing its impact," *IEEE Access*, vol. 8, pp. 90225–90265, 2020.

[3] J. Olsson, D. Hellström, and H. Pålsson, "Framework of last mile logistics research: A systematic review of the literature," *Sustainability*, vol. 11, no. 24, p. 7131, Dec. 2019.

[4] D. Schneider, "The delivery drones are coming," *IEEE Spectr.*, vol. 57, no. 1, pp. 28–29, Jan. 2020.

[5] Q. M. Ha, Y. Deville, Q. D. Pham, and M. H. Hà, "On the min-cost traveling salesman problem with drone," *Transp. Res. C, Emerg. Technol.*, vol. 86, pp. 597–621, Jan. 2018.

[6] M. Mozaffari, W. Saad, M. Bennis, Y.-H. Nam, and M. Debbah, "A tutorial on UAVs for wireless networks: Applications, challenges, and open problems," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2334–2360, 3rd Quart., 2019.

[7] M. Alwateer and S. W. Loke, "On-drone decision making for service delivery: Concept and simulation," in *Proc. IEEE Int. Conf. Pervasive Comput. Commun. Workshops (PerCom Workshops)*, Mar. 2019, pp. 937–942.

[8] E. Frachtenberg, "Practical drone delivery," *Computer*, vol. 52, no. 12, pp. 53–57, Dec. 2019.

[9] W. Fan and X. Jiang, "Tradable mobility permits in roadway capacity allocation: Review and appraisal," *Transp. Policy*, vol. 30, pp. 132–142, Nov. 2013. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0967070X13001352

[10] T. Akamatsu, "A system of tradable bottleneck permits for general networks," *Doboku Gakkai Ronbunshuu D*, vol. 63, no. 3, pp. 287–301, 2007.

[11] T. Akamatsu and K. Wada, "Tradable network permits: A new scheme for the most efficient use of network capacity," *Transp. Res. C, Emerg. Technol.*, vol. 79, pp. 178–195, Jun. 2017.

[12] D. K. Brands, E. T. Verhoef, J. Knockaert, and P. R. Koster, "Tradable permits to manage urban mobility: Market design and experimental implementation," *Transp. Res. A, Policy Pract.*, vol. 137, pp. 34–46, Jul. 2020.

[13] B. N. Coelho, V. N. Coelho, I. M. Coelho, L. S. Ochi, R. Haghnazar, D. Zuidema, M. S. F. Lima, and A. R. da Costa, "A multi-objective green UAV routing problem," *Comput. Oper. Res.*, vol. 88, pp. 306–315, Dec. 2017.

[14] E. Yakıcı, "Solving location and routing problem for UAVs," *Comput. Ind. Eng.*, vol. 102, pp. 294–301, Dec. 2016.

[15] F. Semiz and F. Polat, "Solving the area coverage problem with UAVs: A vehicle routing with time windows variation," *Robot. Auto. Syst.*, vol. 126, Apr. 2020, Art. no. 103435.

[16] W. P. Coutinho, M. Battarra, and J. Fliege, "The unmanned aerial vehicle routing and trajectory optimisation problem, a taxonomic review," *Comput. Ind. Eng.*, vol. 120, pp. 116–128, Jun. 2018.

[17] T. Tomic, K. Schmid, P. Lutz, A. Domel, M. Kassecker, E. Mair, I. Grixa, F. Ruess, M. Suppa, and D. Burschka, "Toward a fully autonomous UAV: Research platform for indoor and outdoor urban search and rescue," *IEEE Robot. Autom. Mag.*, vol. 19, no. 3, pp. 46–56, Sep. 2012.

[18] S. Hayat, E. Yanmaz, and R. Muzaffar, "Survey on unmanned aerial vehicle networks for civil applications: A communications viewpoint," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 4, pp. 2624–2661, 4th Quart., 2016.

[19] M. Y. Arafat and S. Moh, "Routing protocols for unmanned aerial vehicle networks: A survey," *IEEE Access*, vol. 7, pp. 99694–99720, 2019.

[20] A. Trotta, L. Montecchiari, M. D. Felice, and L. Bononi, "A GPS-free flocking model for aerial mesh deployments in disaster-recovery scenarios," *IEEE Access*, vol. 8, pp. 91558–91573, 2020.

[21] T. D. Crocker, "The structuring of atmospheric pollution control systems," in *The Economics of Air Pollution*, H. Wolozin, Ed. New York, NY, USA: Norton, 1966, pp. 81–84.

[22] J. H. Dales, *Pollution, Property & Prices: An Essay in Policy-Making and Economics*. Toronto, ON, Canada: Univ. of Toronto Press, 1968.

[23] C. Egenhofer, "The making of the eu emissions trading scheme: Status, prospects and implications for business," *Eur. Manage. J.*, vol. 25, no. 6, pp. 453–463, 2007.

[24] T. H. Arimura, "An empirical study of the SO_2 allowance market: Effects of PUC regulations," *J. Environ. Econ. Manage.*, vol. 44, no. 2, pp. 271–289, Sep. 2002.

[25] R. G. Newell, J. N. Sanchirico, and S. Kerr, "Fishing quota markets," *J. Environ. Econ. Manage.*, vol. 49, no. 3, pp. 437–462, May 2005.

[26] F. J. Dietz and N. J. P. Hoogervorst, "Towards a sustainable and efficient use of manure in agriculture: The dutch case," *Environ. Resource Econ.*, vol. 1, no. 3, pp. 313–332, 1991.

[27] S. J. Rassenti, V. L. Smith, and R. L. Bulfin, "A combinatorial auction mechanism for airport time slot allocation," *Bell J. Econ.*, vol. 13, no. 2, pp. 402–417, 1982.

[28] S. A. Morrison and C. Winston, "Airline deregulation and public policy," *Science*, vol. 245, no. 4919, pp. 707–711, Aug. 1989.

[29] E. Verhoef, P. Nijkamp, and P. Rietveld, "Tradeable permits: Their potential in the regulation of road transport externalities," *Environ. Planning B, Planning Design*, vol. 24, no. 4, pp. 527–548, 1997.

[30] H. C. Goddard, "Using tradeable permits to achieve sustainability in the world's large cities: Policy design issues and efficiency conditions for controlling vehicle emissions, congestion and urban decentralization with an application to Mexico city," *Environ. Resource Econ.*, vol. 10, no. 1, pp. 63–99, 1997.

[31] H. Yang and X. Wang, "Managing network mobility with tradable credits," *Transp. Res. B, Methodol.*, vol. 45, no. 3, pp. 580–594, Mar. 2011.

[32] Y. Nie and Y. Yin, "Managing rush hour travel choices with tradable credit scheme," *Transp. Res. B, Methodol.*, vol. 50, pp. 1–19, Apr. 2013.

[33] F. Xiao, Z. Qian, and H. M. Zhang, "Managing bottleneck congestion with tradable credits," *Transp. Res. B, Methodol.*, vol. 56, pp. 1–14, Oct. 2013.

[34] A. de Palma, S. Proost, R. Seshadri, and M. Ben-Akiva, "Congestion tolling-dollars versus tokens: A comparative analysis," *Transp. Res. B, Methodol.*, vol. 108, pp. 261–280, Feb. 2018.

[35] J.-T. Wong, "Basic concepts for a system for advance booking for highway use," *Transp. Policy*, vol. 4, no. 2, pp. 109–114, Apr. 1997.

[36] S. Kalmanje and K. M. Kockelman, "Credit-based congestion pricing: Travel, land value, and welfare impacts," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 1864, no. 1, pp. 45–53, Jan. 2004.

[37] Y. Nie, "Transaction costs and tradable mobility credits," *Transp. Res. B, Methodol.*, vol. 46, no. 1, pp. 189–203, Jan. 2012.
[38] X. Wang, H. Yang, D. Zhu, and C. Li, "Tradable travel credits for congestion management with heterogeneous users," *Transp. Res. E, Logistics Transp. Rev.*, vol. 48, no. 2, pp. 426–437, Mar. 2012.
[39] S. Grant-Muller and M. Xu, "The role of tradable credit schemes in road traffic congestion management," *Transp. Rev.*, vol. 34, no. 2, pp. 128–149, Mar. 2014.
[40] D. Fiorello, F. Fermi, S. Maffi, and A. Martino, "Mobility rights for urban road pricing: A modelling analysis with a system dynamics approach," in *Proc. 12th World Conf. Transp. Res.*, Jul. 2010, pp. 11–15.
[41] C. Chiarella and G. Iori, "A simulation analysis of the microstructure of double auction markets," *Quant. Finance*, vol. 2, no. 5, pp. 346–353, 2002.
[42] A. W. Lo and A. C. MacKinlay, "When are contrarian profits due to stock market overreaction?" *Rev. Financial Stud.*, vol. 3, no. 2, pp. 175–205, Apr. 1990.
[43] W. Brock, J. Lakonishok, and B. LeBARON, "Simple technical trading rules and the stochastic properties of stock returns," *J. Finance*, vol. 47, no. 5, pp. 1731–1764, Dec. 1992.
[44] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach* (Pearson Series in Artificial Intelligence). London, U.K.: Pearson, 2019.
[45] B.-J. Kwak, N.-O. Song, and L. E. Miller, "Performance analysis of exponential backoff," *IEEE/ACM Trans. Netw.*, vol. 13, no. 2, pp. 343–355, Apr. 2005.
[46] R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*, 2nd ed. Cambridge, MA, USA: MIT Press, 2018.

FILIPE ALVES NETO VERRI received the B.Sc. degree (Hons.) in computer science and the Ph.D. degree (Hons.) in computer science and computational mathematics from the University of São Paulo, in 2014 and 2018, respectively. He was a Visiting Scholar with the School of Electrical, Computer and Energy Engineering, Arizona State University, under the supervision of Prof. Y.-C. Lai, in 2016. He is currently an Assistant Professor with the Computer Science Division, Department of Computer Methods, ITA. His research interests include data science, machine learning, complex networks, and complex systems.

CESAR A. C. MARCONDES received the Ph.D. degree in computer science from UCLA, in 2008. From 2008 to 2018, he was an Assistant Professor with the Federal University of Sao Carlos (UFSCar) working on Future Internet and Congestion Control. He is currently an Assistant Professor with the Department of Computer Systems, ITA. He also holds industrial patents from USPTO in congestion control while working at Sun Microsystems. His research interests include computer networks and security.

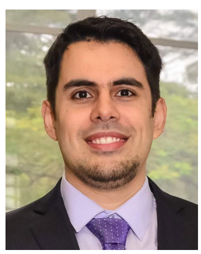
DENIS S. LOUBACH (Member, IEEE) was born in São José dos Campos, São Paulo, Brazil, in 1982. He received the Ph.D. degree in electronic engineering and computer science from the Aeronautics Institute of Technology (ITA), in 2012. From 2014 to 2018, he was an Assistant Professor with the University of Campinas (UNICAMP) working in the area of real-time embedded systems and digital systems. Since July of 2018, he has been an Assistant Professor with the Computer Science Division, Department of Computer Systems, ITA. His research interests include reconfigurable computing, real-time embedded systems, and models of computation theory. He had also worked for a couple of years in the aeronautical industry as an Avionics System and an Embedded Software Engineer.

ELTON F. SBRUZZI received the Ph.D. degree in computational finance from the University of Essex, Colchester, U.K. He is currently an Assistant Professor with the Instituto Tecnológico de Aeronáutica, São José dos Campos, Brazil, since 2018. His research interests include the application of artificial intelligence and data science in business, finance, and economics with focus in aerospace area.

JOHNNY CARDOSO MARQUES (Member, IEEE) received the Ph.D. degree in electronic engineering and computer science in 2016. He is currently an Assistant Professor with the Department of Software Engineering and Information Systems, ITA. His research interests include software quality and testing, requirements engineering, and software standards for regulated environments. He is also a member of IEEE Standards Association. He had also worked for 20 years in the aviation industry and airline companies. He always working with avionics systems and software certification.

LOURENÇO ALVES PEREIRA JÚNIOR received the M.Sc. and Ph.D. degrees in computer science and computational mathematics in 2010 and 2016, respectively. He is currently an Assistant Professor with the Department of Computer Systems, Brazilian Aeronautics Institute of Technology (ITA). He is also a member of the Laboratory of Command and Control and Cybersecurity. His research interests include computer networks and cybersecurity.

MARCOS RICARDO OMENA DE ALBUQUERQUE MAXIMO (Member, IEEE) received the B.Sc. degree *(summa cum laude)* in computer engineering and the M.Sc. and Ph.D. degrees in electronic and computer engineering from the Aeronautics Institute of Technology (ITA), Brazil, in 2012, 2015, and 2017, respectively. He is currently an Assistant Professor with ITA, where he is also a member of the Autonomous Computational Systems Laboratory (LAB-SCA) and leads the robotics competition team ITAndroids. He is especially interested in humanoid robotics. His research interests include mobile robotics, dynamical systems control, and artificial intelligence.



VITOR VENCESLAU CURTIS received the M.Sc. and Ph.D. degrees in electronic engineering and computer science from the Brazilian Aeronautics Institute of Technology (ITA), 2013 and 2018, respectively. In 2017, he was a Visiting Scholar with the Viterbi School of Engineering, University of Southern California (USC) under the supervision of Prof. V. K. Prasanna. Since 2018, he has been an Assistant Professor with the Computer Science Division, Department of Computer Systems, ITA. His research interests include high-performance computing, mathematical optimization, and applied mathematics.