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Market Design for Drone Traffic Management

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Abstract

The rapid development of drone technology is leading to more and more use cases being proposed. In response, regulators are drawing up drone traffic management frameworks. However, to design solutions that are *efficient*, *fair*, *simple*, *non-manipulable*, and *scalable*, we need *market design* and *AI* expertise. To this end, we introduce the drone traffic management problem as a new research challenge to the market design and AI communities. We present five design desiderata that we have derived from our interviews with stakeholders from the regulatory side as well as from public and private enterprises. Finally, we provide an overview of the solution space to point out possible directions for future research.

1 Introduction

Air traffic management (ATM) is currently confronted with the rise of *unmanned aerial vehicles (UAVs)*, so-called *drones*. Advances in battery and materials technology have led to smaller and more agile drones that can carry cargo and equipment (Floreano and Wood 2015). Better communications technology and advances in AI have led to higher drone autonomy and lowered the barrier to entry. This has led to an increase in the number of private drone pilots and spurred R&D efforts into commercial applications (e.g., drone-based delivery services) (Anderson 2017; McKinsey 2019).

Although the airspace for drones is not congested yet, the number of UAVs is expected to radically increase in the coming years (Doole, Ellerbroek, and Hoekstra 2020). It is only a matter of time until drone operators will be competing for airspace, at least in certain locations (e.g., at desirable landing and take-off spots). Scaling up UAV usage to such levels requires well-designed *UAV traffic management (UTM) systems* (i.e., mechanisms that allocate airspace to UAVs).[1] However, such systems are still in their infancy (Barrado et al. 2020; Thipphavong et al. 2018). Designing suitable mechanisms is challenging, given that drones have diverse abilities and drone operators may have diverse preferences. To date, no solution has emerged that convincingly trades off system design desiderata like *efficiency*, *fairness*, *simplicity*, *incentives*, and *scalability*.

While governments around the world are currently revising their UTM regulations (e.g., European Commission (2021); FAA (2020); FOCA (2020)), most of these draw heavily on existing regulations for *manned* ATM, neglecting the particularities of the UAV space. Most importantly, the issue of *strategic behavior* among operators has been largely ignored. This is understandable, given that in (traditional) manned ATM, there are only a few, comparatively similar companies (i.e., airlines), and uncooperative behavior can easily be reprimanded. However, there will be thousands of drone operators, and many of them can be expected to be *self-interested* (i.e., aiming to maximize their own utility). Most UTM proposals allow operators to "reserve" parts of the airspace for free, with the option of cancelling their reservation. The most recent EU regulations, for example, foresee a *first-come-first-serve* mechanism for these reservations (European Commission 2021). Unfortunately, once the airspace is getting congested, such a mechanism would mean that any strategic operator should hurry to reserve as much airspace as they can, as early as possible.[2] Of course, one could limit how many reservations an operator can make, or how often they can freely cancel. However, such "fixes" often introduce their own issues and should not be applied naively. Instead, any UTM proposal should be carefully analyzed before it is employed in practice.

We argue that techniques from *market design* as well as *AI* are most suited to design a UTM system that satisfies all important desiderata (like efficiency and fairness) while also being scalable in practice. Market design is a research area at the intersection of computer science, economics, and operations research, that focuses on the design of well-functioning marketplaces (Kominers, Teytelboym, and Crawford 2017).[3] In particular, using tools from game theory and mechanism design (Myerson 2008), it explicitly takes the strategic behavior of agents into account and aims to design rules that nonetheless lead to good outcomes. Researchers from AI (in particular, from multi-agent systems) have experience with tackling large-scale coordination tasks that require solving complex optimization prob-

[1]In Europe, UTM is commonly referred to as *U-space*.

[2]We further discuss shortcomings of the first-come-first-serve mechanism in Section 3.

[3]The term *market* or *marketplace* refers to a system of rules that allocates goods to agents based on their actions. It does not need to (but can) contain monetary payments (see Section 4.2).

lems (Wooldridge 2009). Over the last 25 years, researchers from market design and AI have successfully tackled some of the most complex resource allocation problems. Prominent examples include spectrum auctions (Cramton 2013), the allocation of courses to students at universities (Budish et al. 2017), and the allocation of vaccines to countries (Castillo et al. 2021). We believe that the design of a good UTM system is a similarly important and exciting challenge.

To understand the challenges in UTM design and derive the most important desiderata, we have interviewed ten stakeholders from regulatory bodies as well as public and private enterprises (see the *Acknowledgements* at the end of this paper). We first describe the UTM design problem in Section 2, before discussing the most relevant market design desiderata in Section 3. Finally, in Section 4, we sketch the space of potential solutions.

2 Problem Overview

The *airspace* is a 4-D space, consisting of three spatial dimensions and one time dimension. *UAV operators* arrive over time and want to complete flights, and each operator has preferences for when and where they fly. A flight is a 4-D trajectory through the airspace. A UTM *mechanism* allocates airspace to self-interested operators. A *feasible* allocation ensures that no two flight paths intersect. Each operator has a certain *value* for their optimal path, but most operators can accommodate deviations at a *cost*. Operators' values and costs are their private information (i.e., only known to themselves) and they act strategically in reporting them.

Drone operators greatly differ in the goals and flexibility of their flights. For example, a wedding photographer may place a high value on flying their drone directly above the wedding, at the precise time the newlyweds exit the building, while any deviation in space or time would drastically reduce their value. In contrast, a delivery drone operator may not care about the exact trajectory of a flight, as long as they reach their destination within a certain time window.

Operators also differ in how they can plan and execute flights, making the *timing* of allocations particularly important. Some operators may want to receive their allocations far in advance (e.g., to plan a photo shoot), while others only know their needs shortly before take-off (e.g., food delivery services) or may desire nondisclosure until the last minute. Operators may have preferences that span multiple flights, e.g., wanting to photograph a certain area on one of several consecutive flights. Preferences may shift as time goes on, and operators may want to submit new flight plans at any point in time. Additionally, while current proposals focus on strategic (pre-flight) allocation and try to keep tactical (in-flight) re-allocation of airspace to a minimum, a UTM mechanism still needs to be robust against events that make dynamic re-allocation unavoidable (e.g., if battery failure or a thunderstorm make flying a particular route impossible).

Any UTM mechanism must also take multiple *practical considerations* into account (Lundberg, Palmerius, and Josefsson 2018). For example, stakeholders agree that public-interest flights (e.g., emergency services, police) must always be *prioritized* over regular participants. Additionally, to ensure *safety*, UAV flight paths need to maintain a minimum spatial and temporal separation from each other and from potential exogenous obstacles (e.g., buildings or bird swarms). This is complicated by the heterogeneous ability of drones and operators to detect and react to threats or changes in their flight plan and varying degrees of aerial maneuverability (e.g., not every drone can "hover" or turn in place). Furthermore, drones differ greatly in their operational range (e.g., some drones may need to maintain line of sight) and maximum flight times (e.g., due to battery capacity). Contrary to the name, not all UTM participants may actually be "unmanned" and any future-proof UTM design needs to also take applications such as (autonomous) air taxis into account. To ensure that proposed UTM systems can cope with any future developments, the market design should be as technology agnostic as possible. However, to operate the market in practice, it is important that UTM designers still take technological constraints into account when specifying regulations. Considering the heterogeneity of the domain, it is desirable that the system is able to directly query individual operators' constraints and requirements.

Depending on the jurisdiction, there may also be *politically imposed side-constraints* regarding noise pollution, privacy, and safety. Any drone flight, no matter how strict the safety regulations, leads to certain risks; concretely, a flight poses a small danger to other drones, to people, and to the infrastructure on the ground. Of course, drone operators have some inherent incentive to fly safely to minimize these risk, because an accident would likely be costly and cumbersome for them and could also lead to stricter regulations being imposed on the drone market as a whole. However, this has limits, as some companies might be more risk-seeking or have shorter planning horizons than their competitors or the regulator. Furthermore, accidents that lead to large collateral damage might simply bankrupt smaller players. Consequently, these players may not fully internalize the externalities they create, forcing a socialization of the resulting costs. Thus, it is important that the regulator defines a *minimum level of safety* on which they are not willing to compromise and which therefore constitutes a hard market design *constraint*. One way to think about this constraint is that safety requirements below this level would endanger the overall health of the drone market and, in the worst case, lead to complete market failure. While higher levels of safety above this minimum are still in the regulator's (and most operators') interest, at that point safety turns from a simple constraint into a desideratum (where more is better) that must be carefully traded off against the other market design desiderata we introduce in the following section.

3 Market Design Desiderata

Based on our stakeholder interviews, we have identified five desiderata that are essential for any UTM mechanism. Not all of these desiderata can be maximized simultaneously (e.g., Parkes (2001, Chapter 2)), such that any UTM design must carefully trade them off against each other.

Remark 1 *There are three different notions for most of these desiderata:* ex-ante*,* ex-interim*, or* ex-post *(Mas-Colell et al. 1995). Ex-ante means that a desideratum holds* *in expectation, given some probability distribution of future world states. Ex-interim means that a desideratum holds while parts of the world have already been realized (e.g., the preferences of a single agent), while others are still uncertain. Finally, ex-post means that a desideratum holds for all possible realizations of the world; thus, it is the strongest notion. However, in a dynamic system, ex-post is often too demanding; but it may still serve as a useful benchmark.*

3.1 Economic Efficiency

A central goal for the design of a UTM system is to ensure that the airspace is used *efficiently*. Efficient markets maximize value creation for participants and tend to attract the largest number of users. However, this raises the question of how to measure efficiency.

The strongest notion of efficiency is to maximize *welfare*. Different notions of welfare exist, the most common being *utilitarian welfare*, i.e., the sum of all operators' values for the allocation (Mas-Colell et al. 1995).

A weaker notion is *Pareto efficiency* (Hammond 1981). An allocation is Pareto efficient if no operator's flight path can be improved without worsening another operator's flight path. This notion is also well-defined when using mechanisms without money. A further relaxation is *non-wastefulness*, which means that there exist no unallocated resources any agent prefers over (parts of) their allocation.

The EU's proposed first-come-first-serve mechanism demonstrates how a mechanism may lead to inefficient allocations even if agents report truthfully. To see this, consider an operator who does not have strong preferences regarding the exact route or time of departure (e.g., a surveyor that could fly at any time during the day). If this operator books far in advance, they may block short-term flights with far higher values for their exact route (such as an urgent delivery). The underlying problem is that the mechanism does not make any trade-off decisions. Thus, the first-come-first-serve mechanism does not maximize welfare and might not even be Pareto efficient.

3.2 Fairness

All stakeholders agree that a UTM system should be *fair*. However, there is no single agreed upon notion of fairness (Chin et al. 2020; Evans, Egorov, and Munn 2020).

To illustrate the challenge in defining fairness, consider the first-come-first-serve mechanism. Some stakeholders see this mechanism as fair, given that all operators have the same chance to be "the first." Yet, this mechanism disadvantages operators that require shorter planning horizons, which may be considered unfair. Next, consider using an auction that allocates the airspace to the highest bidder. Some see auctions as inherently fair, because no operator gets special treatment and only the bids matter. However, others argue that auctions are unfair given that different operators may have greatly varying financial means. While these disagreements cannot be resolved, there are multiple useful concepts for measuring the fairness of market mechanisms. Ultimately, the regulator must decide which notion to optimize for.

One way to measure fairness is via *egalitarian social welfare*, i.e., the minimum utility of any agent. An alternative notion that puts less weight on single agents is *proportional fairness* (Kelly 1997). For an allocation to be proportionally fair, there must not exist another allocation for which the sum of each agent's difference in utility is positive. A last notion is *envy-freeness* (Foley 1966), which means that no agent prefers another agent's outcome. Even though agents have varying preferences, envy-freeness is meaningful as it must hold for *any* possible vector of reports.

3.3 Simplicity

All stakeholders we interviewed have emphasized that a *low barrier to entry* is essential to ensure that the airspace is accessible to diverse types of operators. For market design, this implies that the *user interface* to the marketplace must be sufficiently simple (Seuken et al. 2012). Standard *direct-revelation* mechanisms (Dasgupta, Hammon, and Maskin 1979) would require operators to report their preferences for all possible flight paths, which is obviously impractical. On the other end of the spectrum are mechanisms (like first-come-first-serve) that ask operators to only state their most preferred flight path, and then either approve or reject their requests. Unfortunately, as explained in Section 3.1, this is inherently inefficient, as it does not allow the mechanism to make any trade-offs. A more principled approach involves designing *smart market mechanisms* (Bichler, Gupta, and Ketter 2011) that provide participants with carefully-designed tools that make it easy for them to (dynamically) report the most important aspects of their preferences (Sandholm 2013), while hiding most of the complexity of the underlying market (Seuken, Jain, and Parkes 2010). Here, AI and machine learning techniques may be used to facilitate autonomous path finding (Cieslewski, Choudhary, and Scaramuzza 2018) and to simplify preference reporting (Brero, Lubin, and Seuken 2018).

3.4 Incentives

A key aspect of market design is to ensure that participants have an incentive to report their preferences truthfully. Otherwise, participants may need to spend costly efforts to determine their strategy, and any mechanism that receives manipulated reports will likely make inefficient allocations.

Some of the UTM proposals we have reviewed acknowledge that operators may try to *game* the system (European Commission 2021). But instead of disincentivizing such behavior, the proposals foresee a *monitoring and data gathering approach*, with the goal of detecting any manipulative behavior to then correct the mechanisms accordingly. Unfortunately, this is a flawed approach, because by simply analyzing the data, it may be very hard if not impossible to detect what is going wrong. To illustrate this, consider the *school choice problem*, where students are matched with places at competitive high schools (Abdulkadiroğlu and Sönmez 2003). Many cities employ school choice mechanisms that are highly manipulable, such that it is not optimal for students (or their parents) to rank schools in order of preference. Parents have learned how to optimally manipulate the system, ranking a school first that is attractive while also being likely to accept their child. The result is that, when looking at the data, it *seems* as if the vast majority of students receive their first choice, *suggesting* that the mechanism works almost perfectly, even if this is not at all the case (Abdulkadiroğlu et al. 2006).

Market designers are experts in designing mechanisms that provide participants with good incentives for truthful preference reporting. A very strong desideratum is *strategyproofness* (Nisan 2007), which requires that it is optimal for each participant to report truthfully, no matter what the others report. Strategyproof mechanisms are very desirable, as market participants do not need to engage in complex strategizing, which improves the quality of the information the mechanism receives. One can relax this to *(Bayes-Nash) incentive compatibility*, i.e., an agent cannot benefit from misreporting if all other agents report truthfully.

In practice, it is often impossible to guarantee even Bayes-Nash incentive compatibility, in particular in dynamic environments (Parkes et al. 2010; Bergemann and Välimäki 2019). To this end, researchers have proposed various notions of *approximate strategyproofness* (Lubin and Parkes 2012; Mennle and Seuken 2021; Azevedo and Budish 2019). One can also design mechanisms that are computationally hard to manipulate, which provides a certain notion of robustness (Faliszewski and Procaccia 2010).

Other important considerations are whether a mechanism is *false-name proof* (Yokoo, Sakurai, and Matsubara 2004) (i.e., whether agents benefit from "splitting" themselves into multiple agents) or *collusion-proof* (Ausubel and Milgrom 2006). The latter is important to avoid that incumbent companies coordinate to obtain an advantage over new market entrants. Furthermore, some agents might be *spiteful* (Brandt, Sandholm, and Shoham 2005) (i.e., aiming to minimize the utility of competitors). An example of this would be intentionally taking costly detours in order to saturate a certain part of the airspace with the intention of stopping a competitor from flying. Similar behaviour has been observed in manned aviation (Valido, Socorro, and Medda 2020), making this a potential risk in UTM as well. As spiteful behavior may deter competition, which may lead to monopolization and market failure, opportunities for such behaviors should be minimized as much as possible.

3.5 Scalability

Any UTM system must *scale* well to the ever increasing number of drones. Scalability as a design goal prevents costly system re-designs in the future. To scale well, the system should be intelligent and largely automated, from soliciting operator preferences to allocating airspace.

One concern regarding scalability is the *computational complexity* of the employed mechanisms. For example, even if all preferences were known, finding an optimal allocation is typically $\mathcal{NP}$-hard (Sandholm 2002; Lagoudakis et al. 2005) and therefore potentially untenable for large, congested markets. One possible direction is to simplify the problem and use heuristic algorithms to find near-optimal solutions to the simpler problem (e.g., Dierks, Kash, and Seuken (2021)). Another option is to aim for coarser, congestion-based allocations and rely on individual drones using autonomous collision avoidance (Li, Egorov, and Kochenderfer 2019).

4 Solution Space

In this section, we provide an overview of possible approaches for designing UTM systems. We divide the solution space into three classes: (1) non-market solutions, (2) markets without money, and (3) markets with money.

4.1 Non-Market Solutions

Non-market solutions do not assign airspace based on reports. Examples are rule-based systems defining some topology on the airspace akin to road networks (Sunil et al. 2015; Joulia, Dubot, and Bedouet 2016; Mohamed Salleh et al. 2018), or letting operators autonomously choose their route and avoid collisions. However, since operators have heterogeneous preferences, if the mechanism does not elicit individual preferences, one could end up with a very inefficient allocation or "traffic jams." These approaches are also not able to accommodate well changing numbers of operators or types of routes flown. In an environment that is expected to undergo rapid development in the future, this is not ideal. Another option is to sell off large parts of the airspace to companies who could then re-sell it, similar to what is done for spectrum licenses (Cramton et al. 2002). However, note that this gives the resulting intermediaries a lot of power and also tasks them with solving the difficult market design problem.

4.2 Market-Based Solutions

In a market-based system, operators can make reports about their preferences. These might be *direct revelations* of their full preferences, or more limited, for example by only submitting the ideal flight plan. The airspace can then be allocated based on these reports. The more relevant preference information the mechanism has, the better it can optimize the allocation to achieve the market design desiderata described above (e.g., efficiency, fairness, incentives).

Markets without Money. Market mechanisms do not necessarily require monetary transactions. Prominent examples of *markets without money* include (two-sided) matching mechanisms as used in school choice (Abdulkadiroğlu and Sönmez 2003) as well as (one-sided) assignment mechanisms as used in course allocation (Budish et al. 2017). These mechanisms *do* elicit agents' preferences and then make allocation decisions without charging payments, while still guaranteeing approximate notions of efficiency, fairness, and incentive compatibility. These approaches work well in some settings, for example in schools choice or course allocation, where the students are very homogeneous in their structural needs (e.g., each student is assigned to one school). However, in general, markets without money are relatively limited in their ability to simultaneously achieve multiple desirable properties like efficiency, incentive compatibility and fairness (Zhou 1990; Yenmez 2013; Dughmi and Ghosh 2010).

To handle notions of "urgency" or "importance" (of one flight vs. another), a common approach is to introduce *artificial currency* or *tokens* that operators are assigned by a central entity. These tokens can also be awarded or deducted to reward or punish certain types of behavior within the system, which may help align incentives. A prominent example of such a market is the allocation of food to American food banks (Prendergast 2017). In the context of UTMs, Nakadai (2018) has previously explored this idea. However, one issue that token-based approaches cannot easily solve is that UAV operators may differ greatly in their needs; e.g., some operators may need to make thousands of flights per day while others only want to make one flight per month. To avoid market failure, a large delivery company might therefore require a different number of tokens than a hobby pilot. This raises the challenging question of how many tokens each operator should receive. If one would base the amount of tokens assigned to an operator on the needs the operator *reports*, this would incentivize operators to report higher needs than they actually have. Alternatively, basing token allocation decisions on observable information (e.g., number of flights flown or receipts for drone equipment) would incentivize operators to strategically align their business to inflate this observable characteristic (e.g., flying unnecessary flights). Additionally, any token allocation based on observable information is unlikely to reflect each operator's *actual* needs (e.g., using number of flights flown would disadvantage a wedding photographer with very few, but high value flights).[4] While one way to get around this would be to allow operators to *buy* additional tokens with real money, this would effectively turn the system into a market with money.

Markets with Money. Money can help to make trade-off decisions, which can significantly improve efficiency, while keeping the mechanism fair and incentive compatible. For example, if operators need to pay a larger fee the more space they reserve, then they are incentivized not to reserve more space than they need; but if they urgently need a flight, they can decide to pay more. It is worth mentioning that the focus of a UTM system is not to maximize revenue. Payments should therefore only be as high as is necessary to align incentives. In particular, when the airspace is uncongested, payments could be set to zero or some nominal amount.

Many stakeholders worry that introducing money may present an equity issue, in that players with larger financial value for flights might be able to dominate a market and consistently secure favourable outcomes. However, as has been argued for road pricing, that fear might be overstated (Cramton, Ockenfels, and Geddes 2016). In fact, any revenue that is collected could be used to pay for system costs or could be redistributed to the operators to actually *reduce* inequities between them (Levinson 2010). It is also important to note that having strong financial means and having a high value for a flight are orthogonal to each other. Large, financially strong players with many flights, such as package delivery services, typically have very small profit margins (on the order of cents), implying a small marginal value per flight. Thus, they do not have an incentive to regularly place large bids to compete with operators such as wedding photographers, who have very high values per flight. Finally, by putting different weights on the requests of different operators, one could improve equity to some degree.

Remark 2 *For each of the three dimensions* space, time, and degree of centralization*, different levels of granularity seem possible. A mechanism could assign the entire space at once, or subdivide the space into smaller areas to be treated individually. Similarly, airspace could be allocated for long time periods at a time, or on a minute-by-minute basis. Finally, mechanisms could range from a centralized allocation mechanism, prescribing routes and deviations, to drones negotiating only bilaterally. Centralized solutions make designing for efficiency, fairness and good incentives much easier, but a distributed approach may be necessary to manage computational complexity and allow the system to scale. Research in distributed mechanism design exists, but is scarce (Feigenbaum, Schapira, and Shenker 2007).*

5 Conclusion

In this paper, we have introduced drone traffic management as a market design problem of high practical importance. We have outlined why it is essential for the UTM community (and in particular for regulators) to call on the expertise of AI and market design researchers to ensure that future UTM systems are well designed. For researchers, the next years present a prime opportunity to have a practical impact, as many countries are currently establishing or overhauling their UTM systems. One challenge when trying to influence policy will be to convince policy makers that any new solution offers significant advantages in practice. It will therefore not suffice to only propose and study better mechanisms, but a clear focus also needs to be placed on communicating the advantages and disadvantages of different approaches to audiences outside the research community.

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[4]To address these problems, one may be tempted to simply increase the amount of observable information taken into account, but this would give administrators the impossible task to anticipate all future use cases and correctly assess their importance and value for society.

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