Provisioning of Contention Resolution in Multiple UAVs to Establish Collaborative Tasks

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Abstract. As demand for commercial roles for Unmanned Aerial Vehicles (UAVs) is at its peak, market players are finding it more difficult to accommodate the ever-changing dynamic market requirement. As UAVs are used across multiple verticals such as photography, delivery, providing medical assistance, tracking, etc., the demand has pushed open the floodgates for this sector. UAV platforms today offer only the idea of leasing a drone for a specific period which works well if the requirements are known prior. In the case of an agile environment, the platform services need to incorporate the policy of leasing and releasing UAVs on a need basis. Our paper focuses on the idea of a dynamic UAV as a service platform wherein the UAVs are hired from the public using some selection and provisioning methods. Such a solution will assist in the fast-paced and cost-effective development, but also enable interoperability between multiple companies to share the resources. Regarding this, we have introduced a new contention resolution framework to handle multiple UAVs during the collaborative operation. The proposed framework which comprises a new protocol, task filter, and the application of the Machine Learning (ML) model to perform probabilistic ranking and assign the UAVs for the specific tasks that will address the required situation efficiently.

1. Introduction

Over the last few years, the role of multi-agents like UAV’s have seemingly increased in number and landed as major tools for organizations in the areas of remote asset management, logistics, and public service delivery. UAV’s (like drones) are steadily making inroads into the commercial, consumer, and military sectors. Currently, due to the high prices for the usage of UAVs, and a budding market, companies are unable to find the right balance between the investment in a drone and meeting consumer demands [1]. The goal for these companies is to extend their offerings’ capabilities, create drone fleets, and deliver UAV’s-as-a-service (UAVaaS) to different businesses [2, 3].

Today a UAVs as a service will work only if the demand of the market is known prior [4]. An ad-hoc demand cannot be met immediately unless there is a surplus of UAVs available with the service provider. One of the solutions for this is to lease a public-owned drone to serve the customer for a specific period until there is a demand. In such cases, a solution is required which could enable multiple public-owned drones that have subscribed to the provider to be able to contend for the participation and in turn earn some payment. And this solution should be able to minimize the signaling involved in the publication and subscription of tasks from the customer. When public-owned drones are used for some mission-critical applications, there is a necessity to consider the aspect of security [5]. Moreover, data and service details should be maintained with at most care.

Our solution initially discusses an environment where a network exists with a set of UAVs for a business purpose and how public drones owned by non-members could be leased for tasks in a specific period. The attachment of a public drone for the private applications and make the entire operations secure is the most required one and here we provide the solution which resolves the contention mechanism between multiple UAVs that bid to perform certain tasks collaboratively.

The interesting part of our solution depends on the usage of AI/ML techniques for building a selection and connection methodology for public drones in a dynamic environment. We consider the bidding-based selection which considers various aspects and performs the task allotment based on
assessing the capability of the attached private drones. To address the issues, we have introduced a new contention framework that addresses two strategies in this paper.

i) Secure connection and establishing communication with a public drone – containing attachment contention protocol (in the application layer and not the network layer) which considers the bidding process in earlier selection.

ii) Subsequent knowledge building for future selection.

2. Related Work

The paper [6] addresses the problems of autonomous task allocation and trajectory planning for a fleet of UAVs. It handles the assignment and trajectory problems separately and partially distributed to maintain faster computation. In other work [7], a platform has been proposed to control multiple UAVs and address the new application demands through a simulator. There are works related to UAV as platform services [2, 4] that enable the use of a UAV on a dynamic need basis assigning various tasks. The challenge, however, continues to be the lack of a common extendable framework that incorporates the needs of the customer and the investment on the drones for highly fluctuating market conditions. Today solutions exist on providing drones as a service that could be owned by a private sector like amazon leased to a business [8]. But the stress on the service provider and the customer will be to accommodate those drones into the highly dynamic workload.

Thus, we need a solution to cater to the dynamic needs of the customer without investing heavily in the infrastructure(drones/fleet). We have proposed a new content resolution framework in this paper. This solution is different from the existing attachment protocols as the contention resolution does not happen in the network layer. A 5G network will be provided with the capabilities of attaching a drone to a network [9], however, the solution of contention resolution happens at the application layer depending on the business configuration of the customer on a centralized server or any of the network functions and hence might not be part of 5G as such. The machine algorithm used as a part of the content resolution framework is Combined Regression and Ranking [10]. This method explores the L2-regularized risk minimization procedure for the specific task. It enables the ranking and selection of UAV’s to support the existing multiple UAV’s to perform certain collaborative tasks.

3. System Architecture and Workflow

The overall workflow of the system will involve 7 processes, and a billing database component that enables the data flow in our proposed framework provided in Figure 1.

![Figure 1. Workflow description with various components and functionalities](image-url)
Process 1: Drone resource check – Check the incoming drone to match requirements
Process 2: Drone registration and task allocation – Registration for future reserves and allocations
Process 3: Billing and cost center – Invoice and penalty payments
Process 4: Peer network check – Continuous monitoring inflight
Process 5: Modification request – Request to Modify a task allocation
Process 6: Offload request by drone – Deallocation a task
Process 7: Unregister or service expiry – Retirement of drone from the company network reserves.

Even though all the seven processes will combinedly give a global view of the proposed system. In this paper, we have given more thrust to processes 1 and 2 and the remaining 3 to 7 included here to give an overall view and it may be used for future expansion of our methodology.

3.1 Public drones in a business network

Public drones can attach to the existing business network by using event monitoring. The existing business network decides to outsource tasks involving certain assets to a public system. The drones that wish to act as a service agent subscribes to these event advertisements from the network. On subscription, as a response, the public drone sends across its processing capabilities, storage capacities, and other resource configurations to the network along with a bidding cost per hour of service. The existing business network takes up consensus from the members or owners of the assets on the attachment criteria. Once a threshold number has agreed upon the attachment and cost expenditures, the drone is sent an attachment invite along with the contract on the terms and conditions. The terms and conditions header would have a cost and time of contract wherein the drone would be treated as a property of the existing network. Upon attachment, a new channel is created for the drone, with all the existing members. Transactions in the new channel would be allocated to the drone and the drone would carry out the task. Any deviation in the route or anomaly in the task is detected using an ML model considering the history of missing or improper task reports behavior analysis. If an anomaly is flagged, a consensus is sent to all the existing members for the deletion of the ledger. If the consensus is successful, the ledger is deleted from the drone and saved in a cloud node, which is also a member of the existing business network. The entire process of attachment of UAVs to a company network, starting from bidding to contention resolution to response and future reserve follows the sequence mentioned in Figure 2.

3.2 Sequence Diagram for UAV attachment

![Sequence Diagram for UAV attachment](image)

Figure 2. A sequence of the UAV attachment.
From Figure 2, the primary steps of UAV attachment are described as
a) The public drone subscribes to a private network for task notifications
b) The private network sends task notifications when there is a requirement
c) The public drone bids for the task with the available resources
d) All the requests are pooled, and attachment contention protocol is used to decide the assignment of the task.
e) The network generates a smart contract
f) The smart contract is signed by the private network and the task is assigned.

4. Three-Phased Approach in Contention Framework

New contention protocols and components are introduced to enable security and privacy in this hybrid public-private voluntary offerings for drone services. The proposed system consists of three different phases in a contention framework. The core solution and the novelty of this paper are dealt with the first 2 phases. The third phase is included to provide an end-to-end solution to the problem.

i) Attachment contention protocol is required to resolve which of the subscribed public drones will be selected for serving the customer at this specific point in time for a certain task at hand.

ii) The future reserve is required to minimize the signaling between publish and subscribe to the tasks. When thousands of tasks are flooding the service provider, there will be a huge load on the network with the signaling involved. Hence the future reserve could be used to pick up the right drone for the task.

iii) Task allocation and planning.

4.1 Attachment contention protocol

In this phase, the network publishes a set of requirements for a task along with the upper-cost limit as a broadcast service. Public UAV owners who had subscribed for this service and wish to contend for this to respond with their resource capabilities i.e. (battery, memory, processing, communication capabilities, etc.,) and their time duration of availability. After a contention phase, one UAV is chosen per task based on ML ranking methodologies to collaborate with other UAVs to perform specific tasks that will be explained in detail in Section 5.

4.2 UAV reserve for future tasks

For phase 2, we consider all the UAVs that had bid for the contention (other than the chosen), and for any near future tasks that might occur. This is done by predicting the task occurrences for a fixed time slot (for example an hour) and deriving the probability of usage of these UAVs for that task. The probabilities are sent back to the owners for them to consider keeping the UAV idle for an amount of time. For example, if a UAV receives a 0.98 probability of selection, then the owner can choose to keep the UAV un-occupied for the next one hour as there is a high chance of selection by the same network. This optimizes the need for frequent task broadcasts and reduces significant signaling across the network.

4.3 Task Allocation and planning

Task allocation in such a dynamic environment becomes complex, with the introduction of the time duration of availability. Chosen UAVs should be optimally utilized given their resource capabilities and time duration of availability thereby increasing utilization while minimizing the cost involved in the
system. We also measure how these drones are completing the task in an allotted time without any efficiency issues like battery down, service failure, etc. These issues will be considered and added a penalty during the next time selection. Here the public drones can be involved in the bidding process based on both time and cost and the penalty is also considered as an important parameter for non-selection.

5 Description of Framework with sample illustration

The detailed description of the contention framework will cover the implementation of two different phases with sample illustration: 1- Attachment Content Protocol which enables to resolve the contention between multiple UAVs for selection procedure 2: Distributed Remodeling which has been used as a future reserve of contended UAVs for assignment of incoming tasks. Now we will provide more details for each phase.

5.1 Attachment Contention protocol – Selection of a specific UAV or a set of UAVs for an upcoming requirement in the network.

When multiple drones contend for the same task set, the members of the existing network hold a contention resolution survey and get to vote for the drone to be selected. The probability of successful completion and delivery is determined for each of the incoming nodes based on various features defined by the network. The incoming task requirements would be of the following format as shown in Figure 3.

| Task ID : 1123 |
|---------------|
| TaskType: Medicine delivery |
| TaskLocation: X degrees, Y degrees. |
| Expected Time of delivery: 10minutes |
| Altitude requirement: 10m |
| Time critical: Yes |
| Cost limit: 100 $ |

Figure 3. Example task request

This incoming request is processed by one of the existing nodes in the network which then filters the requirements. Each private drone gets a notification of the above requirements (only those in black color) as part of their subscription alert. The drones that are willing for the bidding cost contend by publishing their information to the network. The following parameters are published by the drone in response to the notification.

- Current location.
- Hours of availability
- Battery and load capabilities
- Computational capabilities
- Drone size and speed.
- Communication capabilities (Bluetooth, embedded with LTE, 5G Network)
- Network ID (if any of previous dialogue with this network)
- Any earlier penalties (derived from the network database using network ID)

In addition to this, a time series prediction is performed, based on the history of transactions, to identify the list of possible task requirements that might appear for a period in the future (for example 1 hour in this case). The time to destination is calculated with the current location of the UAV and the time taken for the UAV to reach a nearby network source and time taken to travel from that source to
the task destination (including a negligible amount of time taken for the content resolution protocol). If any UAV request does not satisfy the time to destination requirements, then an additional filter has applied that checks if the time to destination matches any possible task requirements from the predicted values. If the answer is yes, then the UAV request is retained for further processing.

The UAVs that satisfy the requirement are further processed for the way of contention resolution. In response, the following initial filtering is applied on the UAV and it reverts. In choosing the right UAV, the other parameters mentioned above are analyzed. These parameters are considered as features for the models.

- Battery and load capabilities
- Computational capabilities
- Drone size and speed
- Communication capabilities (Bluetooth, embedded with LTE, 5G network)
- Network ID (if any of previous dialogue with this network)

As shown in Figure 4, depending on the business requirement, the network should derive the weightage required to be complete a task with minimal expenditure dynamically on a real-time basis. Here we also considered the earlier penalties and reducing some weights relate to penalty points.

![Figure 4. Flowchart on requirements handling by the network](image)

### 5.2 Distributed re-modeling technique

For modeling this task, each of the network nodes acts as a representative of one or more features for all the contending drones. The realization of the above mechanism is to represent each feature in a physical node, i.e., each physical node/ UAV can represent one or more features. This helps in distributed re-modeling in case of a dynamically changing network. The main advantage of such a solution is

- to incorporate business requirements of whether to include a feature while modeling can be explicitly provided.
- to distribute the processing load to each node
- to squeeze the neural network architecture on the granular feature level, without influencing the other parameters.
As shown in Figure 5, the task filter component is part of one of the nodes in the case of a decentralized system or the master node in the case of server-client architecture. The purpose of the task filter is to identify the relevant features that would influence the decision of choosing a UAV. For example, from the above features, sometimes the communication capabilities can be a negligible factor for the given task at hand. Hence the task filter can send a “DO NOT REMODEL” command to the node which represents that feature. In this way, the parameter can be ignored by the remodeling process.

At first, it may appear that simply learning a good regression model is enough for this task, because a model that gives a perfect regression will also give a perfect ranking. However, a model with near-perfect regression performance may yield arbitrarily poor ranking performance. We plan to use the machine learning model here. Combined Regression and Ranking method (CRR) \[10\] that optimizes regression and ranking objectives simultaneously. In this Paper, CRR is performed on cumulative features to collate a model to allot a rank for each UAV. We build off the regression and ranking approaches described to create an optimization problem with terms for regression loss \(L(w, D)\) and pairwise ranking loss \(L(w, P)\). In our model, we have assumed the \(\alpha\) value to be 0.60. The detail of the CRR model is provided here.

### 5.3 Combined regression and ranking technique

The goal of supervised regression is to learn a collated model \(w\) that can predict a real-valued target of drone \(y' \in R\) for a feature vector \(x\) like capabilities using a prediction function \(f(w, x)\) with little loss concerning to a specified loss function \(l(y, y')\). Using the method specified in \([10]\), we focus on a form of regression using L2-regularized empirical risk minimization for this specific task. This aggregate loss \(L(w, D)\) is given by:

\[
L(w,D) = \frac{1}{|D|} \sum_{(x,y,q) \in D} l(y, f(w, x))
\]  

(1)

Here, \(l(y, y')\) is a loss function on a single example, defined on the true target value drone \(y\) and the predicted value of another drone \(y'\), and \(f(w, x)\) returns the predicted value of drone \(y'\) using the model represented by \(w\). In this pairwise approach, the original distribution of training examples \(D\) is expanded into a set \(P\) of candidate pairs of a set of drones, and learning proceeds over a set of pairwise example vectors. In general, for fixed \(D\), \(|P|\) is \(O(|D|^2)\), but sharding by query identifier can result in \(|P| \ll |D|^2\). Here, the loss function \(L(w, P)\) is defined over pairwise difference vectors from \(P\) (drones with different feature spaces represented in vector format). Hence, the combined CRR optimization problem is:

\[
\min_{w \in \mathbb{R}^m} \alpha L(w, D) + (1 - \alpha) L(w, P) + (\lambda / 2) \|w\|_2^2
\]  

(2)
Here, the parameter $\alpha \in [0, 1]$ is derived which trades off between optimizing regression loss and pairwise loss. Note that setting $\alpha = 1$ recovers the standard regression problem and setting $\alpha = 0$ addresses the pairwise ranking problem. Setting $\alpha$ to an intermediate value forces the optimization to consider both regression and ranking loss terms.

**Figure 6.** Feature weights calculation algorithm

**Figure 7.** Definition of node

At the end of the modeling cycle, a rank list is obtained based on which the private UAVs are notified. The chosen UAV is notified with a dynamically generated smart contract, which then binds the UAV to the network. The drone with node definition as given in Figure 7 will be selected based on the feature weights as shown in Figure 6.

### 5.4 UAV reserve for future tasks – Additional knowledge capture

We have introduced another important aspect to enhance the bidding process is that the drone could be used as a standby, wherein the drone could be sent back to the owner with a percentage probability of selection. The probability can be used as a decisive factor for the owner to retain the drone on a timely basis without bidding for another network. As shown in Figure 8, For example, if the drone returns with a 0.9 probability of selection with a timeslot of 1 hour, this would mean that there is a 90% chance that this drone might be selected for an upcoming task in the network. The probability of selection is derived based on the history of task usage.

**Figure 8: Two different responses to task bids**

| Task | Task type      | Distance Covered (in kms) | Time taken (in mins) | Resource utilization – memory (in MB) | Battery utilization (in %) | Drone size (in mm) | Time critical | Cost |
|------|----------------|--------------------------|---------------------|--------------------------------------|---------------------------|-------------------|---------------|------|
| Task1| Medicine delivery | 10                       | 10                  | 100                                  | 20                        | 350               | Yes           | 100$ |
| Task2| Groceries delivery | 200                     | 69                  | 50                                   | 50                        | 700               | No            | 10$  |
| Task3| Medicine Delivery | 100                      | 60                  | 90                                   | 90                        | 400               | Yes           | 50$  |
| Task4| Rescue task      | 100                      | 99                  | 200                                  | 100                       | 500               | Yes           | 250$ |
From Table 1, the database indicates the different types of tasks in history and the resource requirements for the same. Let us assume there is a drone in the rank list, that has the resource capabilities as follows,

Resource: 200MB  Battery: 100 %  Bidding cost: 100$  Drone size: 200

Based on history, a probability of upcoming task types are first predicted. And the resource requirements are compared, and a probability of selection is assigned. The task type probability list is provided in Table 2.

| Task type       | Probability |
|-----------------|-------------|
| Medicine delivery | 0.5        |
| Groceries delivery | 0.3      |
| Rescue task     | 0.2        |

Figure 9: UAV ranking flowchart

According to Figure 9, the task requirement will be calculated based on the number of occurrences of a task type in the given period. A time-series regression model with seasonality, daily, or weekly components could be applied to derive this number. For example, task type 1: 20; task type 2: 10, and so on.

Each task type has its own set of requirements, which is also derived based on the history of data. For example, if for a task type “Medicine delivery”, the resource requirements are plotted, and a linear regression model is performed. This predicts the approximate requirement which is then multiplied with the predicted task number. For example: if the predicted requirement is 15MB for task type 1, then the total requirement is calculated to be 15MB & 20 and so on.

5.5 UAV selection probabilities

Based on the task requirements, all the ranked drones are assigned probabilities concerning each other. For example: if 3 UAVs satisfy the requirements and each of them has the same ranking and bidding cost, the probabilities of selection would be 0.33 for each. This would vary depending on the ranking, bidding cost, resource and duration availability, feedback ranking (penalty). Here besides, a penalty will reduce some weights on its selection.
6. Conclusion

The main aspect of the paper introduced a new contention resolution framework between multiple drones with the help of ML/AI techniques by considering the resources of the drone, task requirement from the network, and drone history. There is a smart contract methodology to securely connecting the drone for private applications. Also demonstrated how a drone reserve is maintained by predicting the future task requirements (this is done to minimize the signaling required on arrival of every new task). This enables the creation of a more generalized framework that facilitates the contribution of public-owned UAVs to meet the dynamic task requirements of the company. It facilitates an agile method of provisioning with minimal or no human intervention. As a part of future work, we are planning to device a method for the safe detachment of the drone and focus on security-related aspects of the entire procedure by utilizing the remaining processes provided in our workflow.

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