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AIR TRAFFIC CONTROL AND FLIGHT PLANNING FOR CARGO UAV$_S$ IN A SINGLE AIRSPACE

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Abstract—*This article piece analyzes in detail the challenges and approaches to incorporating large cargo Unmanned Aerial Vehicles into existing airspace, focusing on air traffic management and flight operations planning. Modifications to air traffic control models required as a result of the inclusion of Unmanned Aerial Vehicles are discussed, with a focus on managing the various stochastic parameters that affect flight quality. The importance of maintaining safe takeoff and landing intervals is also emphasized. In addition, the article delves into the application of machine learning techniques in air traffic flow management, exploring the complexities of planning scheduled and special flights under conditions of incomplete information and stochastic uncertainty. The article highlights the importance of optimizing the payload-to-range ratio of Unmanned Aerial Vehicles, taking into account factors such as wind conditions and battery efficiency to improve cargo transport efficiency. In addition, the article presents a two-stage stochastic programming model for flight planning aimed at minimizing costs and efficiently allocating flights and resources. The impact of drones on "last mile" delivery logistics is also discussed, emphasizing the potential benefits of drones in terms of increased speed, cost reduction, and access to remote areas.*

Index Terms—Drone airspace integration; air navigation; flight operation planning; payload-to-range ratio; air traffic control; drone payload efficiency; stochastic flight scheduling; autonomous last-mile delivery.

I. INTRODUCTION

Consider the important management and planning tasks that occur in the practice of civil aviation. Some of the first publications in this area are articles [1] and [2]. Thus, one of the first works was an individual model of automation of air traffic control at the controller level [1], which is still relevant today, but with significant complications in the organization of air traffic at the current level and the development of Global Air Traffic Management (GATM). Such complications are caused primarily by the need to allow Unmanned Aerial Vehicles (UAVs) with large payloads to enter the single airspace. Today, drones can transport small loads without any problems, but a problem arises in the case of large and heavy cargo.

Cargo drones can fly in the same airspace as manned aircraft in accordance with the requirements of the EASA Certified category. Then the flight phases of cargo drones can be presented as shown in Fig. 1.

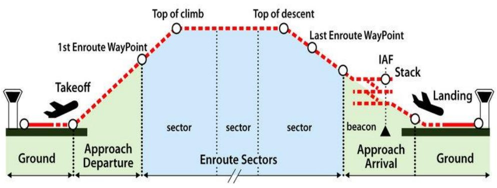

Fig. 1. Flight phases

II. PROBLEM STATEMENT

Let's consider a modified model of flight control and planning, when both the air traffic controller and the remote pilot, who control a set of aircraft taking off or landing, must take into account the random nature of a number of parameters that determine the quality of the task. These include, in particular, the moment when the aircraft appears at the calculated point and the errors in the execution of commands by individual aircraft, which are also affected by external disturbances.

III. PROPOSED METHOD

Suppose that there is a certain set of aircraft in the control area. For each *i*th aircraft from this set, the moment of landing (take off) τ_i is predicted. The moments of two consecutive landings (take offs) τ_{i+1} and $\tau_i \left(\tau_{i+1} > \tau_i\right)$ must be separated in time by at least ΔS_i is the safety interval, which is limited by the echeloning standards. If the safety conditions are not met, it is necessary to change the trajectory or flight mode and delay the aircraft in the control area for a certain time interval t_i. The delay is performed in buffer zones and is also regulated by Air Traffic Flow Management

(ATFM). The choice of the interval t_i must guarantee a given probability of compliance with the safety interval:

$$P\{\tau_{i+1} + t_{i+1} - \tau_i - t_i \geq \Delta S_i\} \geq a_i,\ i = 1, ..., n. \quad (1)$$

Here τ_i is a random variable whose distribution is known.

The pilot, as a rule, cannot realize the delay t_i exactly. Therefore, in inequalities (1), the variables t_i should be considered random variables whose mathematical expectations $\underline{t}_i = Mt_i$ coincide with the aircraft delay intervals in the control area, which are subject to determination and transmission to the board. It is assumed that the distribution function t_i is known to the exact value of $\underline{t}_i$ that is sought.

Of course, the random variables $\tau_i, \tau_{i+1}, t_i, t_{i+1}$ are independent of each other. In this case, knowing the distribution functions of τ_i and t_i, it is easy to calculate the distribution functions of the random variable:

$$\xi_i = (\tau_{i+1} + t_{i+1} - \underline{\tau}_{i+1} - \underline{t}_{i+1}) - (\tau_i + t_i - \underline{\tau}_i - \underline{t}_i).$$

We denote it by $F_i(z) = P(\xi_i < z)$.

We will evaluate the quality of management by the average value of the weighted sum of delays:

$$M\sum_{i=1}^{n} \beta_i \xi_i = \sum_{i=1}^{n} \beta_i \underline{\xi}_i,$$

where the weighting coefficients β_i are assumed to be given. The control conditions and technical constraints on the choice of t_i are specified by inequalities:

$$\underline{\gamma}_i \leq \underline{t}_i \leq \underline{\gamma}_i,\ i = 1, ..., n.$$

Thus, the individual task of automating takeoff and landing control under consideration is reduced to the following stochastic model.

It is necessary to calculate the value of $\underline{t}_i$ delays that are transferred to the of the ith aircraft, for which:

$$\sum_{i=1}^{n} \beta_i \underline{t}_i \to \min,$$

under the conditions:

$$P\{\tau_{i+1} + t_{i+1} - \tau_i - t_i \geq \Delta_i\} \geq a_i,\ i = 1, ..., n. \quad (2)$$

$$\underline{\gamma}_i \leq \underline{t}_i \leq \underline{\gamma}_i,\ i = 1, ..., n. \quad (3)$$

To get the deterministic equivalent of the problem, let's rewrite the conditions (1) in the form:

$$P\{\xi_i < \Delta_i - \underline{\tau}_{i+1} - \underline{t}_{i+1} + \underline{\tau}_i + \underline{t}_i\} \leq 1 - a_i,\ i = 1, ..., n,$$

or the same thing,

$$\Delta_i - \underline{\tau}_{i+1} - \underline{t}_{i+1} + \underline{\tau}_i + \underline{t}_i \leq F_i^{-1}(1 - a_i),\ i = 1, ..., n.$$

We have come to the next linear programming problem:

$$\sum_{i=1}^{n} \beta_i \underline{t}_i \to \min, \quad (4)$$

$$\underline{t}_i - \underline{t}_{i+1} \leq F_i^{-1}(1 - a_i) + \underline{\tau}_{i+1} - \underline{\tau}_i - \Delta_i, \quad (5)$$

$$\underline{\gamma}_i \leq \underline{t}_i \leq \underline{\gamma}_i,\ i = 1, ..., n. \quad (6)$$

Model (4) – (6) is simpler than the model presented in [1] and, unlike it, does not require assumptions about the nature of the distribution of random parameters of the problem conditions, which allows the use of machine learning technologies.

In the process of air cargo transportation, it is necessary to consider a flight planning system [2] that serves two types of flights: regular and special. Scheduled flights are operated between fixed points and are planned in advance. However, plans can be changed within a certain period of time. Special flights occur irregularly, and the time and points of transportation are not fixed in advance. Special flights can be carried out by UAVs operating on regular routes, thereby diverting them from those routes.

Different types of aircraft, both manned and unmanned, differ in payload, flight time, and costs on different routes. Flights are planned with incomplete information. The demand for special transportation is not known in advance. The amount of cargo that arrives over time is based on uncertain parameters of the task conditions. There is a need to reassign aircraft from routes that serve transportation for which the demand is higher than expected. Reassignment may, in particular, be made at intermediate stops. The objective is to minimize the average expected costs over the entire planning period.

The problem is formulated as a two-stage problem with stochastic uncertainty. At the first stage, before the requests for special flights are known, aircraft of each type are allocated to routes and the number of flights of each type on each line is determined. At the second stage, after establishing the realization of the random parameters of the problem conditions, aircraft are reassigned from route to route.

Fixed conditions (conditions of the first stage) limit the total number of flight hours for each type of aircraft distributed over all routes. The restrictions are also related to the existing flight resources for the planned period.

The second stage constraints can be divided into two groups. The restrictions of the first group record the fact that for each type of aircraft, the total number of flight hours transferred from a given route to other lines does not exceed the number of flight hours originally assigned to that route and the ratio of payload to UAV flight range.

The development of the latest technologies optimizes the payload to range ratio of UAVs. The payload-to-range ratio (PRR) for unmanned aerial systems (UAS) is a metric used to evaluate the efficiency and capabilities of a drone in terms of how much payload it can carry in relation to the distance it can travel. It provides an indication of a drone's ability to transport a specific payload over a certain distance, which is especially important for applications such as cargo delivery, surveillance, scientific research, etc.

The formula for calculating the **PRR** (Payload-to-Range Ratiois) as follows:

$$\mathbf{PRR} = \frac{Payload\ Capacity}{Range}. \quad (7)$$

Payload Capacity is the maximum weight of the payload that a drone can carry.

Range is the maximum distance a drone can cover on a single battery charge or fuel tank.

A higher PRR value indicates that the drone can carry more payload over a given distance, which can be useful for applications where payload capacity is a critical factor. However, it is important to note that maximizing PRR is not always the primary goal, as other factors such as endurance, maneuverability, or specific payload requirements may be prioritized for different applications.

When considering payload to range ratios, it is also important to consider factors such as wind conditions, operating altitude, battery life, and propulsion efficiency. These factors can affect the actual performance of the drone and its ability to achieve the specified payload and range.

Therefore, the constraints of the second group, which are common in two-stage problems, such as stochastic programming, are balancing ratios for each route.

We introduce the following notation:

x_{ij} is the number of flights during a certain period of time of aircraft of type i, initially assigned to route j;

x_{ijk} is the number of flights of aircraft type i withdrawn from route j and reassigned to route k;

y_j^+ is the unrealized requests (in tons of cargo) for transportation on route j;

y_j^- is the unloaded capacity of aircraft (in tons of cargo) on the jth route;

a_{ij} is the number of hours required for an aircraft of type i to cover route j if the aircraft was originally assigned to this route;

a_{ijk} is the number of hours required for an aircraft of type i, originally assigned to route j, to cover route k. Obviously, $a_{ijk} \geq a_{ik}$;

b_{ij} is the number of tons of cargo transported per flight by an aircraft of type i on route j;

a_i is the permissible number of flight hours of an aircraft of type i during a month;

d_j is the requests for transportation (in tons of cargo) on route j;

c_{ij} is the cost of a flight of an aircraft of type i on route j, provided that the aircraft was originally assigned to this route;

c_{ijk} is the cost of a flight of an aircraft of type i on route k if it was withdrawn from route j. Obviously, $c_{ijk} \geq c_{ik}$;

$q_j^{(+)}$ is a penalty for failure to fulfill an application for the transportation of a ton of cargo on route j;

$q_j^{(-)}$ is the penalty for underloading by one ton of aircraft on route j.

Let's write the formal model of the problem in the above notation.

The conditions of the first stage, which constrain the total number of flight hours on all routes for each type of aircraft, are as follows:

$$\sum_j a_{ij} x_{ij} \leq a_i, \ \forall_i. \quad (8)$$

To formalize the constraints of the second stage, the following remark should be taken into account. The flight time of an aircraft of type i assigned to route j is a_{ij} hours. If this aircraft is reassigned to route k, then it will take a_{ijk} hours to overcome this route. Thus, this flight on route k causes the cancellation of a_{ijk} / a_{ij} flights on route j.

The conditions of the second stage of the first group, which mean that it is impossible to cancel more flights of aircraft type i on route j than were originally scheduled for this route, are written in the form:

$$\sum_{k\neq j}\frac{a_{ijk}}{a_{ij}}x_{ijk}\forall_i. \quad (9)$$

The conditions of the second group of the second stage are as follows:

$$\sum_i b_{ij}x_{ij}+\sum_i\sum_{k\neq j}b_{ik}x_{ikj}-\sum_i\sum_{k\neq j}\left(b_{ij}\frac{a_{ijk}}{a_{ij}}\right)x_{ikj} + y_j^+ - y_j^- = d_j, \forall_j. \quad (10)$$

These are the balance conditions that determine transportation requests and their fulfillment.

The target functionality of the two-stage flight planning problem is expressed as follows:

$$\sum_{i,j}c_{ij}x_{ij}+M\left\{\min x_{ikj},y_j^+,y_j^-\left[\sum_i\sum_{k\neq j}\left(c_{ijk} - c_{ij}\frac{a_{ijk}}{a_{ij}}\right)x_{ikj}+\sum_j\left(q_j^+y_j^+ + q_j^{(-)}y_j^-\right)\right]\right\}. \quad (11)$$

Thus, the flight planning problem is reduced to a two-stage stochastic programming model, in which it is necessary to calculate the nonnegative parameters $x_{ij}, x_{ijk}, y_j^+, y_j^-$ that minimize the objective function (11) under the conditions (8) – (10). The variables x_{ij} and x_{ijk} are also subject to an additional requirement of integer integrity.

Representing flight planning as a two-stage model is a certain idealization of the problem. A more natural description of the situation can be presented by means of a multi-stage stochastic programming problem, which would consistently take into account daily changes in transportation requests. However, solving a multi-stage flight planning problem is associated with significant computational difficulties. We propose the following way to simplify the problem.

We divide the planning horizon into n periods and represent the situation as a sequence of two-stage stochastic programming models. The solution obtained for a sequence of two-stage problems can be considered as an approximate solution to a multi-stage flight planning problem.

The optimal plan of the problem for period t determines the initial information for the next period:

$$x_{ij}(t+1)=x_{ij}(t)-\sum_{k\neq j}\frac{a_{ijk}}{a_{ij}}x_{ijk}(t)+\sum_{k\neq j}x_{ikj}(t). \quad (12)$$

To the uncertain transportation requests to be received in period t are added requests for cargoes that were received but not transported in previous periods. A penalty is introduced for the delay of cargo by l periods.

The problem of the tth period minimizes the total costs associated with reassigning flights, losses due to late cargo, fines for unfulfilled transportation requests, and underutilization of aircraft.

The problem domain is described by constraints on the available aircraft fleet and on the cargo capacity of each type of aircraft on each route. In addition, the model conditions include the usual balance relations for a two-stage problem and inequalities of the form (9) typical for reassignment problems.

It can be assumed that the outlined sequence of two-stage problems allows us to obtain a fairly good approximation to optimal flight planning with significantly less computational complexity than a multi-stage stochastic programming problem.

Consider how drones affect the efficiency of last-mile logistics. While first-mile delivery is the beginning of the supply chain, last-mile delivery is the end of the supply chain. The introduction of drones into the last-mile logistics industry has revolutionized the process of delivering goods to customers. First-mile operations ensure the delivery of goods from the manufacturer through the courier to the carrier. Last mile operations are completed when the order is delivered.

In the context of transportation, supply chain, manufacturing, and retail, the last mile is used to describe the delivery of products as the last stage of transportation, the performance of which is determined:

a) faster delivery and greater convenience attract consumers;

в) increased sales and revenues: deliveries to remote and rural areas, their sales and profits can increase due to better access to new customers;

c) increased efficiency: Last-mile delivery can help businesses optimize their operations by reducing the time and resources required for delivery. Using automation and digital technology, manual labor and administrative tasks can be eliminated, leading to more efficient and profitable delivery operations.

In this case, drones can reduce the time and costs associated with last-mile delivery, as well as improve the quality of customer service and thus increase the efficiency of goods logistics. This means maximizing the ratio of the beneficial effect to the cost of obtaining it.

In this respect, drones have become a powerful asset in the last-mile logistics industry, allowing for shorter delivery times and, as a result, increased efficiency in this industry. This is due to the fact that

1) drones can travel faster than traditional delivery vehicles because they don't need roads or traffic;

2) they can deliver goods directly to the customer's location;

3) drones can be programmed to fly autonomously, which reduces the need for manual labor and shortens delivery times;

4) drones can be used to access previously inaccessible areas. For example, drones can be used in rural areas that are difficult to reach by road. This makes it easier for companies to deliver goods to these areas and provides customers with a more efficient delivery service;

5) the ability to track and control the delivery process in real time. Companies can use drones to track the location of a parcel as well as to determine the status of delivery. This provides customers with greater visibility into the delivery process and helps companies better manage their operations;

6) due to the ability to cover large areas regardless of terrain, drones can approach dangerous areas, such as high voltage zones, without endangering people and allowing for more informed decisions during adverse incidents;

7) drones are used to improve the safety of last-mile logistics. Drones can be used to monitor the areas around a delivery location, ensuring that the delivery is made safely and the customer's property is protected. In addition, drones can be used to detect intruders and, if necessary, alert the appropriate personnel.

IV. Conclusions

All of this enables companies to reduce delivery costs and increase customer satisfaction by providing faster delivery services. Therefore, the problem of urgent delivery of goods can be viewed as an automated system with queuing objects with events that occur at random moments in time. Such events form a stochastic sequence, usually called an event stream.

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Лі Хаоян, В. П. Харченко. Керування повітряним рухом та планування польотів вантажних БПЛА в єдиному повітряному просторі

У статті детально проаналізовано виклики і підходи до включення великих вантажних безпілотних літальних апаратів в існуючий повітряний простір з акцентом на керуванні повітряним рухом і плануванні польотів. Розглянуто модифікації моделей керування повітряним рухом, необхідні в результаті включення безпілотних літальних апаратів, з акцентом на керуванні різними стохастичними параметрами, що впливають на якість

польотів. Також підкреслюється важливість дотримання безпечних інтервалів зльоту і посадки. Крім того, в статті розглядається застосування методів машинного навчання в керуванні потоками повітряного руху, досліджуються складнощі планування регулярних і спеціальних рейсів в умовах неповної інформації та стохастичної невизначеності. У статті підкреслюється важливість оптимізації співвідношення корисного навантаження до дальності польоту безпілотного літального апарату з урахуванням таких факторів, як вітрові умови та ефективність батарей для підвищення ефективності вантажних перевезень. Крім того, в статті представлена двоетапна модель стохастичного програмування для планування польотів, спрямована на мінімізацію витрат і ефективний розподіл польотів і ресурсів. Також обговорюється вплив дронів на логістику доставки "останньої милі", підкреслюються потенційні переваги дронів з точки зору збільшення швидкості, зниження витрат і доступу до віддалених районів.
Ключові слова: інтеграція повітряного простору безпілотників; планування польотів; співвідношення корисного навантаження до дальності польоту; керування повітряним рухом; ефективність корисного навантаження безпілотників; стохастичне планування польотів; автономна доставка «останньої» милі.

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